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Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables

Mario Hernandez Tinoco, Nick Wilson *

Credit Management Research Centre, Leeds University Business School, The University of Leeds, Leeds LS2 9JT, United Kingdom

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ABSTRACT

Using a sample of 23,218 company-year observations of listed companies during the period 1980–2011, the paper investigates empirically the utility of combining accounting, market-based and macro-economic data to explain corporate credit risk. The paper develops risk models for listed companies that predict financial distress and bankruptcy. The estimated models use a combination of accounting data, stock market information and proxies for changes in the macro-economic environment. The purpose is to produce models with predictive accuracy, practical value and macro dependent dynamics that have relevance for stress testing. The results show the utility of combining accounting, market and macro-economic data in financial distress prediction models for listed companies. The performance of the estimated models is benchmarked against models built using a neural network (MLP) and against Altman's (1968) original Z-score specification.

1. Introduction

The financial crisis of 2008 highlighted the shortcomings of risk management practices within the lending environment and risk assessment at the micro level (PD estimation). Lenders and other investors in the corporate sector along with regulators require timely information on the default risk probability of corporates within lending and derivative portfolios. For banks, developing effective 'Internal Rating Systems' (IRB) for corporate risk management requires building probability of default (PD) models geared to the specific characteristics of corporate sub-populations (e.g. SME's, private companies, listed companies, sector specific models), tuned to changes in the macro environment, and, of course, tailored to the availability and timeliness of data. The use of credit risk models has been well documented since Altman (1968). There is now an extensive literature on the modelling of corporate financial distress and bankruptcy but often, it reports work that is either based on using publically available historical accounting data (Altman, 1968) or relies on securities market information (Merton, 1974) to predict insolvencies. Recent papers argue for a combined approach. Trujillo-Ponce, Samaniego_Medina, and Cardone-Riportella (in press) test both accounting and market data (Credit Default Swaps, CDS) and suggest that "accounting and market data complement one another and thus a comprehensive model that includes both types of variables appears to be the best option." (p. 2). The outcome definition, bankruptcy, is taken from formal (legal) insolvency notices, debt servicing (Mella-Barral & Perraudin, 1997) and bond (Geske, 1977) or loan defaults, default swaps[1] (Ericsson, Jacobs, & Oviedo, 2009) or stock market suspensions. These modelling approaches have been applied extensively to listed companies using statistical procedures such as MDA, logistic regression or hazard models. Recent work has extended the definition of bankruptcy to include wider measures of 'financial distress' based on financial statements. Further, attempts have been made to incorporate some dynamics by the inclusion of data reflecting changes in the macroeconomic environment, non-financial data and other time variant predictors. The present study contributes to the academic literature by, first, presenting distress prediction model for quoted companies in the United Kingdom that employ a 'finance-based' definition of distress, to detect early stages of financial distress, alongside the more formal approach using event data provided by the London Share Price Database. Timely prediction of financial distress could, in practice, help creditors avert some of the costs associated with a bankruptcy filing. Second, using a multi-level theoretical and empirical procedure, this study offers a financial distress prediction model that, with a rather small number of variables, exhibits a considerably high classification and prediction accuracy relative to previous research works. Third, and perhaps most importantly, the study tests, for the first time in financial distress prediction models for public companies in the United Kingdom, the relative contributions (individual as well as collective) of three types of variables: financial ratios, macroeconomic indicators, and market variables.

The paper is structured as follows. In the next section we discuss the literature that is relevant to our modelling approach. We describe

* Corresponding author. Tel.: +44 1133434472.
E-mail addresses: busmhe@leeds.ac.uk (M. Hernandez Tinoco), nw@lubs.leeds.ac.uk (N. Wilson).

[1] The issuance of (rated) bonds and the related CDS market is relatively small among UK listed companies and therefore not considered in this study.

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our database and measures of the outcome variable and set of explanatory variables. The estimation methodology is discussed along with analysis, results and conclusions.

2. Review of the literature

Most of prior default prediction models for quoted companies employ a definition of the criterion event that is contingent upon its ultimate legal consequence: either bankruptcy in the United States and creditors' compulsory and/or voluntary liquidation in the United Kingdom. These are highly visible legal events that can be objectively and accurately dated for use as an outcome variable. The likelihood of bankruptcy can be modelled using binary choice models that require that the populations of failing and non-failing firms be well defined and clearly separated from each other.[2] However, this legal definition of default is not without issues. For instance insolvency can be a lengthy legal process and the 'legal' date of failure may not represent the 'economic' or the 'real' event of failure. Analysis of UK companies demonstrates a considerable time gap (up to three years or 1.17 years in average) between the period that a firm enters a state of financial distress (that caused the firm to default) and the date of legal default/bankruptcy. This evidence is consistent with the finding by Theodossiou (1993) that firms in the United States stop providing accounts approximately two years before the bankruptcy filing. The implication is that a firm in this situation is already in serious financial distress at some point two years before the legal bankruptcy event. Moreover, it is possible that a firm in a state of financial distress does not change the legal status that a bankruptcy filing would entail (Balcaen & Ooghe, 2004). Additionally, changes in insolvency legislation, (e.g. the Enterprise Act 2004 in the UK or Chapter 11 in the US) which have attempted to create a 'rescue culture', have changed the nature and timing of the legal bankruptcy process. Wruck (1990) states that there are several stages that a firm can go through before it is defined as dead: financial distress, insolvency, filing of bankruptcy, and administrative receivership (in order to avoid filing for bankruptcy), for instance. Moreover decline can be managed by the sale of assets (pre-packs) and eventual dissolution rather than formal bankruptcy.

The present study introduces for the first time, for quoted companies in the United Kingdom, a definition based on 'financial distress'. This development has been highlighted as important in the academic literature (Barnes, 1987, 1990; Pindado, Rodrigues, & De la Torre, 2008) and is justified by the fact that the failure of a firm to meet its financial obligations does not inevitably lead to a filing of bankruptcy. The study recognises that financial distress can be costly for creditors and that they would wish to take timely actions to minimise/avert these costs. It is therefore essential that a reliable financial distress prediction model be developed that not only uses the event of bankruptcy as the primary outcome, but also includes the time when a company fails to meet its financial obligations. Wruck (1990) defines financial distress as the situation where the cash flow of a firm is not enough to cover its current financial obligations.[3] Asquith, Gertner, and Scharfstein (1994) analyse the options that junk bond issuers face in order to prevent bankruptcy and define financial distress in a similar way. Their definition of financial distress is based on interest coverage ratios. In practical terms, a firm is classified as financially distressed if its earnings before interest, taxes, depreciation and amortisation (EBITDA) are less than its reported financial expenses (interest expense on debt) for two consecutive year beginning in the year following its junk bond issue, or, if in any other year, EBITDA is less than 80% of its interest expense. Similarly, Andrade and Kaplan (1998) define financial distress as the first year that a firm's EBITDA is less than financial expenses. However, the authors classify firms in this category (in addition to the first condition) whenever a firm attempts to restructure its debt, or defaults. The fulfilment of any of these conditions classifies a firm as financially distressed. Whitaker (1999) analyses the early stages of financial distress and points out that its effects are not limited to those firms that are unable to meet contractual debt obligations as they come due, but also to those firms whose likelihood of default increases. He states that, in fact, the effects of financial distress can be detected before the firm defaults, as a proportion of the loss in firm value occurs before default or bankruptcy. Whitaker (1999) defines financial distress as the first year in which a firm's cash flow[4] is less than current maturities of long-term debt. Moreover, market value is used in order to confirm financial distress i.e. whether the distressed firms in the sample had either a negative rate of growth in market value or a negative rate of growth in industry-adjusted market value.

Previous research has tested the utility of market variables in predicting bankruptcy by employing methodologies such as the Black and Scholes (1973) and Merton (1974) contingent claims or option based approach. Bharath and Shumway (2008), Hillegeist, Keating, Cram, and Lundstedt (2004), Reisz and Perlich (2007), and Vassalou and Xing (2004) have employed the contingent claims approach to estimate the likelihood of corporate failure. More recently data on Credit Default Swaps (prices and spreads) have been used to proxy credit risk (Alexander & Kaeck, 2008). Many empirical papers have attempted to demonstrate the superiority of market-based models over accounting-based models and vice versa. However, the results obtained from these models (that entail numerous restrictive assumptions[5]) and the subsequent performance comparisons with accounting-based models have been controversial. In a recent paper, Agarwal and Taffler (2008) perform a comparison of market-based and accounting-based bankruptcy prediction models, and find that traditional models based on financial ratios are not inferior to KMV-type, option-based models for credit risk assessment purposes. They conclude that, 'in terms of predictive accuracy, there is little difference between the market-based and accounting models.[6]' Hillegeist et al. (2004) provide contrasting results indicating that the Black–Scholes–Merton option-pricing model provides significantly more information about the probability of bankruptcy that do either the Altman's Z-score or the Ohlson O-score. As surmised earlier the default prediction literature can be characterised by a competing approach, where there is a clear division between market and accounting variables. Hillegeist et al. (2004),[7] for instance, recommend that researchers use the Black–Scholes–Merton methodology instead of the traditional accounting-based measures as a proxy for the probability of bankruptcy.

More recent work suggests that both approaches yield similar results implying that both contain useful information about firms' likelihood of default/financial distress. Furthermore, the individual characteristics (e.g. timeliness) of each type of variable (market and accounting) give promise to the development of a model that is superior in performance than ones that rely on *either* accounting *or* market variables. Balcaen and Ooghe (2004)[8] argue that 'if researchers only include financial ratios into their failure prediction model, they implicitly assume that all relevant failure or success indicators – both internal and external – are reflected in the annual accounts.[9]' It is clear

[2] Balcaen and Ooghe (2004, p. 21).

[3] Such as debts to suppliers and employees, and principal or interest payments in arrears.

[4] Defined as net income plus non-cash charges.

[5] The underlying assumptions of the theoretical Merton–Black–Scholes option-pricing model are, according to Saunders and Allen (2002) and Agarwal and Taffler (2008): normality of stock returns, and the existence of a single zero coupon loan (it does not distinguish between different types of loans), for instance.

[6] p. 1550.

[7] p. 28.

[8] Argenti (1976), Zavgren (1985), Keasey and Watson (1987), and more recently Maltz, Shenhar, and Reilly (2003) offer support for the inclusion of non-financial variables to default prediction models.

[9] Balcaen and Ooghe (2004, p. 35).

that financial statements do not include all the information that is relevant to the prediction of financial distress, and market variables are very likely to complement this deficiency.

Rees (1995) suggests that market prices might be a useful predictor for the probability of bankruptcy as they include information on future expected cash flows. For Hillegeist et al. (2004) the stock market is an alternative source of information because it contains information from other sources in addition to the financial statements. Beaver, McNichols, and Rhie (2005) indicate that a probability of bankruptcy is embedded in market prices, even though this probability might not be directly extracted: 'as the probability of bankruptcy increases the non-linear nature of the payoff function for common stock becomes increasingly more important because of risky debt and limited liability.'[10] Clearly the inclusion of market-based variables is appealing on several grounds: first, market prices reflect the information contained in accounting statements plus other information not in the accounting statements (Agarwal & Taffler, 2008), making them a comprehensive mix potentially useful for the prediction of corporate default. Second, the inclusion of market-based variables can considerably increase the timeliness of prediction models; while financial accounts are available in the United Kingdom on a quarterly basis, at best (prior research have used annual data conventionally), market prices are available on a daily basis. Third, market prices might be more appropriate to predict bankruptcy, as they reflect future expected cash flows (accounting statements, in contrast, reflect the past performance of the firm). And fourth, market-based variables can provide a direct assessment of volatility, a measure that could be a powerful predictor of bankruptcy risk and that is not contained in financial statements. According to Beaver et al. (2005) the notion is that the greater the volatility, the higher the likelihood of bankruptcy.

Among the few studies that include a set of market variables to enhance the timeliness and power of distress prediction models are Campbell, Hilscher, and Szilagyi (2008), whose analysis examines the determinants of failure as well as the pricing of financially distressed stocks with a high probability of failure through a logit model that includes accounting and market variables. In addition to a set of two accounting variables, several market variables are tested: the monthly log excess return on each firm's equity relative to the S&P 500 index, the standard deviation of each firm's daily stock return over the past three months, the relative size of each firm measured as the log ratio of its market capitalisation to that of the S&P 500 index, and the firm's log price per share truncated above at $15. The estimates of the study are computed with United States data for public companies.

Similarly, Chava and Jarrow (2004) test in their analysis, in addition to the Altman's (1968) accounting variables, the variables included in Shumway (2001): the accounting variables net income to total assets and total liabilities to total assets; and the market variables: relative size defined as the natural logarithm of the firm's equity value in relation to the total NYSE/AMEX market equity value, yearly excess returns calculated as the firm's cumulative monthly return minus the value-weighed CRSP NYSE/AMEX monthly index return, and the stock's volatility computed as the standard deviation using the last sixty observable daily market prices. In Shumway (2001) the same market variables are tested in a bankruptcy prediction model with some minor variations, namely the idiosyncratic standard deviation of each firm's stock returns, whose value is computed by regressing each stock's monthly returns on the value-weighted NYSE/AMEX index return for the same period (year). More recently, Christidis and Gregory (2010), follow Campbell et al. (2008) and test three market variables in a distress prediction model for UK quoted companies that includes also a set of accounting variables. As to the market variables, they replace book value of assets with market values and test whether log semi-annual excess returns over the FTSE All Share Index and firm stock returns' standard deviation (calculated over a six-month period) can enhance the predictive power of the model. Their findings suggest that market values have the ability to increase the accuracy of the distress prediction model.

The incorporation of time variant data into credit risk models that captures changes in the macro-economic environment is important in two main respects. First it adds a dynamic element to the models that acts to adjust risk scores (likelihood of insolvency) in relation to changing macro-economic conditions. Second such models would have a built-in facility to stress test PD estimates across the portfolio. There are few studies that have incorporated a macro-dependent hazard into the equations (Mare, 2012; Nam, Kim, Park, & Lee, 2008; Qu, 2008). In this paper we control for macro conditions, inflation and interest rate changes, over the sample period.

In the next section we describe the database used in the study, the construction of our outcome variable and the selection of independent variables.

3. Database descriptions and outcome definition

The panel data for the study consists of 23,218 company year observations for a total of 3020 non-financial publicly quoted companies, an average of around 8 annual observations per company. The period covered by the observations in the database ranges from 1980 to 2011.

3.1. Outcome definition

The promised analysis requires a definition of financial distress, which can be viewed as the outcome of a process. In line with earlier discussions and recent papers we focus on the ability of a firm to repay its financial obligations (Asquith et al., 1994). We develop an ex-ante model for estimating financial distress likelihood following Pindado et al. (2008) which employs two main conditions that need to be met in order to detect and predict financial distress in a given firm/year (observation): a firm is classified as financially distressed,[11] i) whenever its earnings before interest and taxes depreciation and amortisation (EBITDA) are lower than its financial expenses for two consecutive years; and ii) whenever the firms suffer from a negative growth in market value for two consecutive years. With regard to the first condition, if EBITDA is lower than the interest expense on the company's debt then it can be concluded that the operational profitability of the firm is not sufficient to cover its financial obligations; on the other hand, with reference to the second condition, Pindado et al. (2008) state that the market as well as stakeholders are likely to judge negatively a firm that suffers from the operational deficit (described in the first condition) until an improvement in the financial condition is perceived again. Thus, the fall in market value for two consecutive years is interpreted as an indication that a firm is in effect in financial distress. As in Pindado et al. (2008), the study is thus introducing a dynamic approach, a novel development in existing financial distress definitions. The variables Earnings before interest and taxes depreciation and amortisation (EBITDA) and Interest expense on debt were obtained from Thomson One Banker. In order to compute the changes in market value for the companies in the database, the present study used the information available in both Thomson One Banker and Datastream.[12]

However, this study recognises the need to include an indicator of default in addition to the previous 'finance-based' definition of dis-

[10] p. 110.

[11] In a general logit model a firm is considered as financially distressed in the year that immediately follows the occurrence of both events by assigning a value of 1, and zero otherwise.

[12] Both databases were used as some missing information on specific companies in one database could be completed by the data of the other. A merging of the databases was therefore required in order to obtain larger time series and thus a more accurate model.

tress in order to complete the concept of financial distress and therefore enhance the scope and the discriminating/predictive power of the model for practical purposes. A definition based on Christidis and Gregory (2010) is utilised. Thus, a firm is classified as being in financial distress not only when it meets the previous two conditions, but also when it is deemed to have formally defaulted on its obligations. The definition of the outcome variable was constructed using the information available in the 2012 London Share Price Database (LSPD). A firm is defined as in default/financial distress whenever its status is defined as suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm.

Thus, a firm is classified as financially distressed when its LSPD (2012) status is equal to any of the following definitions (that indicate the reason why the security ceased to be quoted in the SEDOL): 6) Suspension/cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended — if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was/is being distributed; 16) Receiver appointed/liquidation. Probably valueless but not yet certain; 20) In Administration/Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless. In addition, the present analysis also tracks the specific date when each one of these events occurs.

For simplicity, in the remainder of this study, the binary dependent variable including both of the above definitions of corporate failure and financial distress will be referred to as 'financial distress indicator'. Accordingly, all firms classified as failed or financially distressed, will be referred to as 'financially distressed' or in 'financial distress.' Among the total number of observations, there are 1254 firm-years classified as financially distressed; yielding a proportion of 5% of annual observations in financial distress (Table 1). The available accounting data was taken from Datastream and Thomson One Banker (Worldscope); the macroeconomic variables were collected from Datastream; and the market variables were constructed merging the information available from Datastream, the London Share Price Database and Worldscope. Market information was added to the companies that were found in the Thomson One Banker database. The merging of the accounting and market variables in one database resulted in fewer firms having both complete market-based time-series than accounting information.

Table 2 presents the summary statistics for the 379 failed firms that were classified according to the definition of corporate failure in this study using the 2012 LSPD database. Among the 381 failed companies, 379 were used for the calculation of summary statistics.[13] Panel B in Table 2 shows that, among the companies that form the sample of failed firms; there is a lag that ranges from 0 to 36 months before the date of failure. In other words, firms in financial difficulty, that eventually fail, cease providing accounts 1.17 years in average before the date of failure. The minimum lag of months is zero (meaning that the company that fails keeps providing accounts until the date of failure) and the maximum observed lag is 36; one firm in the sample ceased providing official accounts 3 years before failure.[14]

[13] Two companies were removed as they presented a lag in the number of months that was much higher than that observed for the maximum in the present sample of failed firms. As such, both firms were considered as extreme observations (outliers) that can have an abnormally high influence on the results, and were therefore not employed in the calculation of the summary statistics presented in Table 2.

[14] A likely explanation for this considerable lag is that the firm might already be facing serious financial stress at the time it ceases to provide accounting information and is therefore attempting to defer the accounts in order to prevent its financial state from deteriorating any further or from a suspension of the trading of its stock on the main exchange where it is quoted, which can be very costly.

Table 1
Summary statistics for annual observations. Financially and not financially distressed firms.

Classification of annual observations into financially and not financially distressed firms.			
NFD	FD	Total	%FD
21,964	1254	23,218	5.0%

Notes: This table reports summary statistics for the entire sample used in the construction of the financial distress prediction model. NFD and FD are financially and not financially distressed firms. %FD is the proportion (in percentage) of annual observations that meet the financial distress criteria of the study. The criteria used to classify firms into financially and not financially distressed firms are as follows. A firm is classified as FD when it files for bankruptcy (definition constructed using the London Share Price Database, see details below), or whenever it meets both of the following conditions: i) its earnings before interest and taxes depreciation and amortisation (EBITDA) are lower than its financial expenses for two consecutive years and, ii) there is a negative growth of its market value for two consecutive periods.

In specifying the models there are two main objectives. First, the intention is to build more accurate and timely financial distress prediction models, using data that is routinely available. The models are designed to obtain more accurate results compared to previous works in the academic field and are constructed with a parsimonious approach since they are intended to have practical value. Further, Zmijewski (1984) and more recently Pindado et al. (2008) have shown that in fact a large set of variables is not required for the models to reach their maximum level of efficiency. Pindado et al. (2008), for instance, employ a set

Table 2
Summary statistics of corporate failure of UK firms.

Panel A: classification of failed UK quoted companies				
Obs	N	F[a]	Total	%F
23,218	2641	379	3020	12.6%
Panel B: failed companies: lag of months between the date of failure and the last available account				
N	Min	Max	Mean	STD
379	0	36	14.21	4.82

Notes: Panel A reports summary statistics for the firms in the last stage of financial distress, corporate failure. Obs is the total number of observations (firm-years) in the database, N is the number of normal (non-failed) firms, F is the number of failed firms according to the definition below, Total is the number of firms in the database, and %F is the proportion (in percentage) of failed firms relative to the Total number of firms in the database. The definition of corporate failure (that follows the approach of Christidis and Gregory (2010)) was constructed using the information available in the 2012 London Share Price Database (LSPD). A firm is classified as failed when its status in the 2012 LSPD is defined as: suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm.[b] Panel B reports the lag of months between the date of failure of the company and the last available account. N is the number of failed companies that were classified as failed according to the above 2012 LSPD definition of corporate default, Min is the minimum number of months observed among the failed companies, and Max is the maximum observed number of months. The table also shows the Mean (14.21 Months or 1.17 years approximately) and the standard deviation (STD).

[a] For the purposes of the analysis, firms classified as failed in the database are assigned a value of 1, and zero otherwise according to the date of failure. Accordingly, the failed firms are included among the 1254 financially distressed indicators in the database.

[b] The LSPD numbers and definitions in the database are: 6) Suspension/cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended — if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was/is being distributed; 16) Receiver appointed/liquidation. Probably valueless but not yet certain; 20) In Administration/Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless.

of only three accounting variables to reach a high level of accuracy in their financial distress prediction model. The variables employed in their study are the ratios earnings before interest and taxes over total assets, financial expenses to total assets, and retained earnings to total assets, which represent profitability, financial expenses, and retained earnings, respectively. Zmijewski (1984) uses a set of accounting variables that includes proxies for return on assets, financial leverage, and liquidity. Moreover, in a study that intends to investigate the empirical relation between risk of bankruptcy and systematic risk through the construction of a single composite score that reflects the ex-ante probability of bankruptcy for a company at a given point in time, Dichev (1998) employs a measure derived from exiting accounting models such as the 5-variable Altman (1968) Z-model, and the 7-variable Ohlson (1980) logit model.

The second objective of the analysis is to test the usefulness of other non-accounting variables, namely macroeconomic and market variables, with regard to their contribution to the accuracy and timeliness of financial distress prediction models for quoted companies. We investigate whether macroeconomic and market variables enhance the discriminating and predicting power of the models. There have been very few studies that analyse the performance of these three kinds of variables in a statistical financial distress prediction model. It is deemed important to investigate macroeconomic and market variables since the former is potentially useful to act as a complement to the accounting variables and the latter adjusts estimated scores in relation to changes in the macro-economic environment and provides the facility to impose stress testing scenarios.

Of course, accounting data can only be obtained on an annual basis, so even if the discriminating power of some previous and widely used models (such as the Altman (1968) model) is quite high, there is always the risk of the relying on out dated information. Furthermore, through a detailed analysis of the most extreme form of financial distress,[15] corporate failure, the present study shows that the firms that were classified as failed,[16] stop providing accounting data one year on average (14 months) before the actual date of failure.

From the database, consisting of 130 variables in total, several accounting, macroeconomic, and market variables were tested. The final variable selection is reported below. The selection method relied on previously reported results, theoretical propositions and empirical assessments. The data was subject to a rigorous cleaning and testing process and a novel approach for dealing with outlying observations was adopted. Using both univariate and multivariate (logit) procedures considerable experimentation was undertaken to arrive at the final choice of regressors. The variable selection included four accounting ratios: Total Funds from Operations to Total Liabilities, Total Liabilities to Total Assets, the No Credit Interval, and Interest Coverage; two macroeconomic variables: the Short-Term Bill Rate (inflation-adjusted or deflated), and the Retail Price Index (base 100). Four market variables were found to considerably increase the prediction accuracy of the model: the firm's stock price, the company's yearly abnormal returns, the firm's size relative to the total size of the FTSE All-Share market value, and the ratio Market Capitalisation over Total Debt. These are discussed in detail below.

Due to the existence of extreme values of variables for some observations in most databases (that could significantly alter the results of the analysis), the present study uses, for the first time in a financial distress prediction model, the hyperbolic tangent transformation (TANH transformation) to provide a satisfactory solution to this recurrent issue in preference to frequently used technique of windsorising[17] the outliers in a dataset. According to Godfrey (2009), when using this statistical tool, the real line is mapped for a range of $[-1,1]$, and where x possesses a small value, then $\tanh(x) \approx x$. Therefore, TANH can be used to generate a linear transformation for input values located near 'expected' values while reducing values that are outside the expected range (Godfrey, 2009).[18]

3.2. Independent variable selection

3.2.1. Accounting ratios

A range of potential independent variables were selected and tested based on extant empirical studies. With regard to the accounting variables four ratios: Total Funds from Operations to Total Liabilities, Total Liabilities to Total Assets, the No Credit Interval, and Interest Coverage were selected. The variable, Total Funds from Operations to Total Liabilities (TFOTL), funds flow ratio that represents a performance measure, was built using the data available in Worldscope. Total Funds from Operations represents the sum of net income and all non-cash charges or credits; it is the cash flow of the firm. The denominator of the ratio, Total Liabilities, is composed of all short and long-term liabilities acquired by the company. This variable has been successfully employed in other studies, e.g. Marais (1979) in a Bank of England Study, and Ohlson (1980). This ratio is intended to show the extent to which a company is able to generate funds from its operations to meet its financial obligations. The real line of TFOTL can be mapped onto $[-1,1]$, where a positive value indicates a good position of the firm with regard to its financial obligations and a negative value suggests that a firm might be in a position where it does not generate sufficient funds from its operations to comply with its acquired obligations and might default. The higher the value of this financial ratio, the less likely it is for a company to be in a distressed financial position. A negative sign for this ratio is expected, confirming the above hypothesis that a higher value of this ratio (approaching 1) decreases the probability of financial distress (the estimate's sign should be negative).

The ratio Total Liabilities to Total Assets (TLTA) is a measure of financial leverage. The data used to produce this variable was also taken from Worldscope (as was the case of most of the accounting ratios in this study). Total Liabilities, as discussed, is composed of all short and long term liabilities acquired by a company. The denominator, Total Assets of industrial firms, is the addition of total current assets, long-term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets. The ratio is commonly used to measure a firm's financial leverage (and therefore financial risk) by calculating the proportion of the company's assets that have been financed using short and long-term debt. Zmijewski (1984) included TLTA (represented as FINL) in a three-variable accounting model, where it displayed the expected sign and was statistically significant. More recent studies, such as Shumway (2001) and Chava

[15] The term in quotes is borrowed from Christidis and Gregory (2010, p. 6).

[16] The definition of the response variable was constructed using the information available in the 2012 London Share Price Database (LSPD). A firm is defined as failed whenever its status is defined as suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm.

[17] The setting of all outliers to a specific percentile of the data. For instance, they typical 90% Winsorisation would set all the data below the 5th percentile to the value located in the 5th percentile. Similarly, all of the data above the 95th percentile would be set equal to the value located in the 95th percentile.

[18] The hyperbolic function $\tanh(x)$ has been used and tested in robust signalling processing as well as in statistical estimation, and it has been shown to be very useful to decrease the effect of extreme values of a specific variable. It has been demonstrated that outlying cases can lead to abnormally large residuals and have an atypical impact on the fitted maximum likelihood linear predictors resulting from binary logistic regression models. Thus, the failure to effectively treat outliers could lead to a critical misrepresentation of the validity of the inferences drawn from the models. The values transformed using the TANH function range from -1 to 1, and for small values of x, $\tanh(x) \approx x$. Thus, 'with appropriate scaling, TANH can be used to provide a linear transformation for input values in the neighbourhood of 'expected' values while reducing values that are outside the expected range.' (Godfrey, 2009, p. 1).

and Jarrow (2004) in the United States, and Christidis and Gregory (2010) in the United Kingdom, have tested it and confirmed its consistency and contribution to default/bankruptcy prediction models. The real line of TLTA can be mapped onto [−1,1], where an increasing large, positive value indicates an increasing leverage of the firm. Moreover, the higher the leverage, the higher the financial risk taken by the firm and therefore the higher its probability of financial distress. This is because a highly leveraged company (a high TLTA ratio) could find itself in a very difficult and perilous position if creditors demand the repayment of the contracted debt. Likewise, a small or negative value of the accounting ratio TLTA should indicate that the assets of the firm are financed by equity instead of debt. A positive sign of the variable's estimate is therefore expected in the analysis, signifying that a high value of the ratio (a high leverage) should have a positive impact in the probability of financial distress. In the present analysis, it is investigated whether the ratio TLTA is able to enhance the accuracy of new financial distress prediction models for UK quoted companies.

The variable No Credit Interval (NOCREDINT) is intended to measure liquidity (Agarwal & Taffler, 2007; Taffler, 1983). Graham (2000) defines the No Credit Interval variable as 'an estimate of the length of time that a company could finance the expenses of its business, at its current level of activity, by drawing on its own liquid resources and on the assumption that it made no further sales.'[19] The input required to produce this accounting variable was taken from Worldscope: Quick assets, Total Current Liabilities, Sales, Earnings Before Interest and Taxes, and Depreciation. The NOCREDINT variable was calculated with the following formula: (Quick assets minus Current liabilities) / (Daily operating expenses). Where Quick Assets represent the assets that can be quickly and easily converted into cash or are already in cash form. The formula employed to calculate Quick assets is Current Assets minus Inventories. Similarly, Daily operating expenses are equal to (Sales minus Earnings Before Interest and Taxes minus Depreciation) / 365. The number resulting of this formula is, as expected, the number of days that a company can finance its expenses by drawing on its own current resources. However, as previously explained, the ratio was transformed using the TANH function in order to treat the problem of outlying values of the variable that could have an abnormal impact on the fitted maximum likelihood linear predictors as well as on the size of the residuals that resulted from the binary logistic regression. After the TANH transformation, the real line of the NOCREDINT variable can be mapped onto [−1,1], where an increasing large, positive value indicates an increasing capacity of the firm to finance its business expenses with its quasi-liquid and liquid resources given its current level of activity. Conversely, a small or negative value of this variable suggests a precarious liquidity position of the firm potentially leading to a stressed position with regard to its financial obligations. A negative sign of the No Credit Interval variable's estimate is expected, suggesting that a high value of the variable should have a negative impact on the firm's probability of financial distress.

The final accounting ratio is Interest Coverage (COVERAGE) and measures a firm's ability to pay interest on outstanding debt (Altman & Sabato, 2007). The Interest Coverage ratio was therefore calculated dividing the variable Earnings before interest, taxes and depreciation (EBITDA)[20] by the variable Interest charges or Interest expense on debt that represents the service charge for the use of capital before the reduction for interest capitalised. Typically, a value smaller than 2–2.5 suggests that the firm might be having trouble meeting its financial obligations; a value below this threshold should therefore be considered as a serious warning sign: The firm is not creating enough cash from its operations, as measured by its Earnings before interest, taxes, and depreciation (EBITDA), in order to meet its interest expenses on debt. A value greater than 2.5 is interpreted as the firm being able to generate funds from its operations to meet interest payments. In the present study, the COVERAGE ratio was also transformed using the TANH function in order to treat the problem of outlying values of the variable that could have an abnormal impact on the fitted maximum likelihood linear predictors as well as on the size of the residuals that resulted from the binary logistic regression. After the TANH transformation, the real line of the COVERAGE variable can be mapped onto [−1,1], where an increasing large, positive value indicates an increasing ability of the firm to meet its debt obligations. A negative sign of the COVERAGE variable's estimate is therefore expected, suggesting that a high value of the variable should have a negative impact on the firm's probability of financial distress of failure.

3.2.2. Macro-economic variables

In addition to the accounting ratios, two macroeconomic variables were selected (among a list of eleven macroeconomic indicators) and included in the final model: the Retail Price Index (RPI), and the United Kingdom Short Term (3-month) Treasury Bill Rate Deflated (or the real short term Treasury bill rate), both are represented on an annual scale in the present study. The first macroeconomic variable, the Retail Price Index indicator, a measure of inflation, was taken from Datastream (the Office for National Statistics being the primary source), and it is defined by Thomson Financial as 'an average measure of change in the prices of goods and services bought for the purpose of consumption by the vast majority of the households in the UK.' The Retail Price Index is compiled and published monthly. There are just a few default/failure prediction studies where this variable has been tested, and its relationship with the probability of default has varied. As a measure of inflation, and thus as a 'hidden risk pressure' that acts as an incentive for those disposing of savings to invest them rather than see their purchasing power erode further in the future through inflation, it could be expected that the risk-taking capacity of investors increases in the same direction, lowering thus a firms' probability of default, as discussed by Qu (2008). However, as acknowledged by the same author, the direction of the relationship inflation-probability of default has not been unequivocally established due to the 'complexity of inflation's effect on the economy.'[21] Mare (2012), on the other hand, develops a failure prediction model for banks and founds that the measure of inflation employed is positively related to the probability of default. His rationale is that high inflation is rather the consequence of a generally weak macroeconomic environment, which in turn increases the number of banking crises. Now, as there is a direct relationship between the banking and the industrial sector, whose magnitude is dependent upon the choice of capital structure adopted by firms (the proportion of debt to equity), the present study's hypothesis is that a high RPI should increase a firm's probability of failure. A positive sign of the RPI variable's estimate is therefore expected, suggesting that a high value of this variable should have a positive impact on the firm's probability of financial distress of failure.

The second macroeconomic variable included in the model is the Short Term Treasury Bill Rate Deflated (SHTBRDEF), which represents the 'real' short-term rate of 3-month United Kingdom Treasury Bills on an annual basis. Two main sources were used to construct this indicator: from the Bank of England website[22] the level of the discount rate from 1985 to 2011 was obtained; and from Datastream, the inflation rate employed in order to deflate the discount rate for the same

[19] p. 86.

[20] EBITDA measures the earnings of a firm before interest expense, income taxes and depreciation. Worldscope calculates EBITDA by taking the pretax income and adding back interest expense on debt and depreciation, depletion and amortisation and subtracting interest capitalised.

[21] p. 194.

[22] http://www.bankofengland.co.uk.

period. Treasury Bills are defined as 'bearer Government Securities representing a charge on the Consolidated Fund of the UK issued in minimum denominations of £5000 at a discount to their face value for any period not exceeding one year'.[23] Treasury Bills are typically considered as the least risky investment available. They are much more liquid than gilts (with maturity ranging between 0 and 15 years) and therefore the yield rate on treasury bills is normally lower than on longer-term securities. The present study included the annualised level of the 91 days (3-month) discount rate in order to test another measure intended to capture the state of the macroeconomic environment that could potentially have an effect on the probability of financial distress of industrial companies. This indicator is a proxy for interest rates, which, similar to the RPI variable, is very likely to affect industrial firms according to their capital structure. Lower interest rates facilitate businesses to borrow in order to invest in new equipment, inventories, building, research and development, etc. Furthermore, it is well known that the firm's expected return on investment is higher today when rates are low than when they are high, which acts as an incentive for businesses to invest more when they operate in a low interest rate environment. Business borrowing is perhaps the most affected by high interest rates; firms might be in need to recur to short term loans in order to offset temporary or cyclic short-falls in expenses, payroll, etc., thus a high level of interest rate make the cost of debt more expensive, as companies will have to pay more interest back to their lenders. It is therefore assumed that a high value of the level of SHTBRDEF will increase the probability of failure. A positive sign of the SHTBRDEF variable's estimate is therefore expected, suggesting that a high value of this variable should have a positive impact on the firm's probability of financial distress of failure.

3.2.3. Market variables

The study included four market variables in the models in order to test whether they increase the predictive power of an accounting and macroeconomic model. The first one is the firm's equity price (PRICE). Equity prices data was obtained from the Datastream database. The implicit underlying assumption used in the present study to justify the inclusion of market equity prices in the models is that they reflect a wide mix of public information concerning the future cash flows that can be expected from a company's share and, as suggested by Rees (1995), 'a subset of that information will be relevant to the likelihood of liquidation and the cash flow impact.'[24] Therefore, it is expected that equity prices contain relevant information about the probability of financial distress even if they are not a direct measure of that probability (Beaver et al., 2005). It is also assumed that market prices will act as a complement to the financial statement and macroeconomic information by enhancing the predictive power of the general model, and not as competing or mutually exclusive alternatives that should be used in isolation. The reason is that equity prices incorporate financial statement data as well as other information publicly available as inputs, potentially making markets a more efficient processor of all available public information than accounting data alone (Rees, 1995) and therefore increasing the overall accuracy of financial distress prediction models. It is assumed that the financial position of the firm may lead to portfolio realignments that affect and adjust equity prices ahead of the financial distress event. Furthermore, Beaver et al. (2005), suggest that 'as the probability of bankruptcy increases, the non-linear nature of the payoff function for common stock becomes increasingly more important because of risky debt and limited liability.'[25] Nevertheless, it might be also the case that some equity prices incorporate random information that is not directly relevant to the financial distress or insolvency process, as discussed by Rees (1995), and that this might introduce noise into the analysis and impair the predictive accuracy of the model. However, there have been studies where equity prices have had a positive effect on the predictive power of the model (Beaver, 1966; Beaver et al., 2005; Christidis & Gregory, 2010). Moreover, the superior predictive accuracy of a distress prediction model is not the only potential benefit drawn from the inclusion of equity prices; the timeliness of the models could also be greatly improved (Keasey & Watson, 1991). Accordingly, to the extent that market prices reflect investors' expectations of future cash flows or earnings, and that the company's earnings are affected by its financial position, it is expected that there is a close relationship between price levels/movements and the probability of financial distress. It is therefore assumed that a high value of the level of PRICE will decrease the probability of financial distress. In other words, a negative sign of the PRICE variable's estimate is therefore expected, suggesting that a high value of this variable should have a negative impact on the firm's probability of financial distress or failure.

The second market variable included in this study is the lagged cumulative security residual return (ABNRET). In order to incorporate this variable in a financial distress prediction model, each firm's past residual return[26] in year t was calculated as the cumulative monthly return of the twelve months prior to the year where the financial distress event was observed, minus the FTSE All Share Index cumulative monthly return for the same period ($t-1$). Moreover, as with the previous financial statement and macroeconomic variables and in order to confirm its predictive ability, the ABNRET variable was computed as the cumulative monthly returns two years prior to the observation of the financial distress event ($t-2$). Both of the variables required to construct ABNRET (Firm's monthly returns and FTSE All Share Index monthly returns) were taken from the Datastream database. The ABNRET variable was also transformed using the TANH function in order to treat the problem of outlying values of the variable that could have an abnormal impact on the fitted maximum likelihood linear predictors as well as on the size of the residuals that resulted from the binary logistic regression. After the TANH transformation, the real line of the ABNRET variable can be mapped onto $[-1,1]$, where an increasing large, positive value suggests a lower probability of financial distress. Following Shumway (2001), the theoretical underlying assumption used in the present study to justify the incorporation of lagged residual returns into the models is that they should be useful to predict failure as investors discount the equity of those firms that are in a stressed financial position or close to bankruptcy/default. Furthermore, ass discussed by Beaver et al. (2005), if the option-like feature of common equity is accurate, where equity can be interpreted as a call option on the assets of a company (the face value of the liabilities being the strike price), then the value of common equity acts as the 'equity cushion available to debt-holders before their principal and interest become jeopardized.' Therefore, a decline of the value of equity (and thus a diminished equity cushion) should entail a higher probability of failure/financial distress. This hypothesis is consistent with the findings of Dichev (1998), who measures bankruptcy risk employing the Altman (1968) and Ohlson (1980) models, and shows that there is a negative association between equity returns and the likelihood of bankruptcy. Accordingly, it is posited that high firms' returns relative to the FTSE All Share Index returns will decrease the probability of financial distress. In other words, a negative sign of the ABNRET variable's estimate is therefore expected, suggesting that a high value of this variable

[23] Definition taken from Datastream, Thomson Financial.

[24] p. 310.

[25] p. 110.

[26] In order to calculate residual/abnormal returns, firms' individual returns are employed as the main input. The investment return can be defined as the total gain or loss on an investment over a given period of time. The return incorporates the change in the asset's values plus any cash distributions (dividends or interest payments). The specific Datastream datatype used in the present study is the Total Return Index (RI) which shows 'a theoretical growth in value of a share holding over a specific period, assuming that dividends are reinvested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date.'

should have a negative impact on the firm's probability of financial distress or failure.

The third market variable incorporated to the model represents the Size of the company measured by its market capitalisation relative to the total size of the FTSE All Share Index (in order to make size static). The information required to construct this specific variable was taken from the Datastream database where the index Market Value (MV) is calculated as the sum of the share price multiplied by the number of ordinary shares in issue for each index constituent.[27] In the present study, the variable SIZE, was calculated as the logarithm of each firm's size relative to the total market value of the FTSE All Share Index. The minimum value drawn from this method of calculation was −16.60 and the maximum value −2.37, with an average equal to −10.05. This range of values results from the fact that the logarithmic form of a small number (a firm market value relative to that of the FTSE All Share will result in a very small value) yields a negative sign. Firm size as measure by the market value can be a potentially powerful predictor of failure if the option-like feature of common equity is used again as a theoretical framework; the market value of equity of a firm in a stressed financial position is discounted by market participants (investors) which entails a reduction in the debt holders 'equity cushion.' This decline in the level of equity, induced by a negative investors' judgement of the firm's financial standing, can systematically move towards the 'strike price' (or the value of liabilities) until it reaches the point where it is insufficient to serve the firm's debt obligations (and the firm defaults). As suggested by Agarwal and Taffler (2008) 'the probability of bankruptcy is the probability that the call option will expire worthless or, in other words, that the value of the assets [as measured by the firm's market value, the size] is less than the face value of the liabilities at the end of the holding period.'[28] Therefore, it is predicted that a high value of the SIZE variable should entail a low probability of failure/financial distress. Conversely, a relatively small-sized company should have a higher probability of financial distress. In other words, a negative sign of the SIZE variable's estimate is therefore expected, suggesting that a high value of this variable should have a negative impact on the firm's probability of financial distress or failure.

The final market variable that entered the final model is the ratio Market Capitalisation to Total Debt (MCTD). The variable Market Capitalisation was taken from Datastream whereas the variable Total Debt was taken from Thomson One Banker (Worldscope). Total Debt is equal to all interest bearing and capitalised lease obligations. As specified by Thomson Reuters, it is the sum of long and short term debt. This market variable was adjusted using the TANH function in order to solve the problem of outlying values. The real line of MCTD can be mapped onto [0,1], where a high value indicates that there is considerable scope for a decline in value of a firm's assets (as measured by the market value of equity) before its total debt exceeds its assets and it becomes financially distressed or insolvent. Conversely, a low value of the variable indicates that the firm's decline in value is very close to reaching the point of insolvency, or the point where its total debt exceeds its assets. The higher the value of this financial ratio, the less likely it is for a company to be in a distressed financial position. Thus, it is posited that a high value of the MCTD variable should entail a low probability of failure/financial distress. Conversely, a low value company should involve a higher probability of financial distress. In other words, a negative sign of the MCTD variable's estimate is predicted, suggesting that a high value of this variable should have a negative impact on the firm's probability of financial distress or failure. Other than the market value dimension (that previous default prediction models in the United Kingdom have failed to incorporate), this variable is intended to solve an important problem highlighted in Beaver et al. (2005), namely that the variables ABNRET, and specially SIZE, used in this study, are not 'scaled in that [they are] not compared with the magnitude of debt outstanding.'[29] The case of the variable SIZE should be particularly stressed as it is measured by the company's market capitalisation relative to the total market capitalisation of the FTSE All Share Index (transformed employing the logarithmic function). It could be therefore argued that the variables MCTD and SIZE, having the same denominator, could be highly correlated giving rise to a multicollinearity problem that may affect the stability of the coefficients of the independent variables in response to marginal changes in the model and/or data. Correlation matrices were computed and presented in Table 3 along with other diagnostic tests.[30]

4. Methods: panel logit model specification

The sample is divided into two groups, financially distressed firms (either financially distressed or insolvent in law) and normal or non-financially distressed firms. The outcome is a binary dependent variable. Our approach is to model the outcome within a panel logit framework (Altman & Sabato, 2007; Altman, Sabato, & Wilson, 2010), and follow Shumway (2001) and Nam et al. (2008) who show that a panel logit model, that corrects for period at risk and allows for time varying covariates,[31] is equivalent to a hazard model.

The logistic regression model is as follows. Let (Y_1, Y_1), …, (Y_n, X_n) be a random sample from a conditional logit distribution. Next, let x_{1j}, x_{2j} … x_{kj} be a collection of k independent variables denoted by the vector $\mathbf{x}'$. Assuming that each of these variables is at least interval scaled and that the conditional probability that the outcome is present is denoted by $\Pr(Y = 1|\mathbf{x}) = \boldsymbol{\pi}(\mathbf{x})$ then the logit of the logistic regression model is denoted by:

$$g(\mathbf{x}) = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1^0 X_{1j} + \boldsymbol{\beta}_2^0 X_{2j} + \ldots + \boldsymbol{\beta}_k^0 X_{kj}$$

and

$$\boldsymbol{\pi}(\mathbf{x}) = \frac{\exp g(\mathbf{x})}{1 + \exp g(\mathbf{x})}$$

then

$$\Pr\left[Y_j = 1|\mathbf{x}'\right] = \boldsymbol{\pi}(\mathbf{x}) = \\ = \Pr\left[Y_j = 1|X_{1j}, \ldots X_{kj}\right] = \frac{1}{1 + \exp\left(-\boldsymbol{\beta}_1^0 X_{1j} - \ldots - \boldsymbol{\beta}_k^0 X_{kj}\right)} =$$

[27] In Thomson Reuters' 2008 'Datastream Global Equity Indices.' User Guide. Issue 5. p. 20. For companies with more than one type of common/ordinary share, market capitalisation represents the total market value of the company.

[28] p. 1543.

[29] p. 111.

[30] Multicollinearity is present when there is linear dependency among two or more independent variables in a multivariate model. This problem arises because some of them may be measuring the same concept. Consequently, when a given independent variable is a linear or a quasi-linear combination of other independent variables, the affected estimates are unstable and the standard errors inflated. Tolerance value and is reciprocal, variance inflation tests are computed as $1 - R_k^2$ and $1/(1 - R_k^2)$ respectively, where R_k^2 is the determination coefficient for regression of the ith regressor on all the other regressors. Freund and Littell (2000) show how the instability of the coefficient estimates is increased by the existence of multicollinearity. It must be mentioned that there is not a formal criterion to establish a VIF value threshold above which multicollinearity can be ascertained; it has been argued that a VIF value greater than 10 suggests significant collinearity. The VIF values of all the regressors incorporated in the present study's models, show they are all even below 5, which indicates that multicollinearity is not present in the models and that the levels of the coefficients obtained are therefore reliable.

[31] Shumway (2001, p. 123).

Table 3
Correlation matrix and multicollinearity diagnostic statistics.

Variable	TFOTL	TLTA	NOCREDINT	COVERAGE	RPI	SHTBRDEF	PRICE	ABNRET	SIZE	MCTD
Panel A: correlation matrix										
TFOTL	1.00000									
TLTA	0.17057	1.00000								
	<.0001									
NOCREDINT	−0.09720	−0.44510	1.00000							
	<.0001	<.0001								
COVERAGE	0.72613	0.02865	−0.05983	1.00000						
	<.0001	<.0001	<.0001							
RPI	−0.19100	−0.12218	0.14404	−0.19691	1.00000					
	<.0001	<.0001	<.0001	<.0001						
SHTBRDEF	0.12491	0.09343	−0.10688	0.11610	−0.81383	1.00000				
	<.0001	<.0001	<.0001	<.0001	<.0001					
PRICE	0.37131	0.05951	−0.04823	0.37641	−0.19656	0.15184	1.00000			
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001				
ABNRET	0.25785	−0.06960	0.03254	0.29870	−0.04405	−0.05138	0.28852	1.00000		
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001			
SIZE	0.36300	0.09781	−0.08105	0.40685	−0.23538	0.10799	0.58264	0.29448	1.00000	
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
MCTD	0.08792	−0.34893	0.18940	0.13136	−0.04910	−0.00248	0.20164	0.23896	0.22630	1.00000
	<.0001	<.0001	<.0001	<.0001	<.0001	0.7461	<.0001	<.0001	<.0001	
Panel B: multicollinearity diagnostic statistics										
TOL	0.49947	0.77183	0.87329	0.47709	0.31558	0.32067	0.60705	0.81705	0.58202	0.77601
VIF	2.00214	1.29562	1.14509	2.09603	3.16874	3.11847	1.6473	1.22391	1.71817	1.28865

Notes: Panel A of this table reports the correlation matrix of all the variables included in the model. It includes financial statement ratios, macroeconomic indicators, and market variables. *p*-Values represent the probability of observing this correlation coefficient or one more extreme under the null hypothesis (H0) that the correlation (Rho) is zero. Panel B reports the values resulting from tests intended to detect the presence of multicollinearity among all the variables incorporated in the model: Tolerance value (TOL) and its reciprocal, Variance inflation (VIF) are computed as $1 - R_k^2$ and $1/(1 - R_k^2)$ respectively, where R_k^2 is the determination coefficient for regression of the *i*th regressor on all the other regressors.

therefore

$$\Pr\left[Y_j = 1|X_{1j},\ldots X_{kj}\right] = \frac{1}{1+\exp\left(-\sum_{i=1}^{k}\beta_1^0 X_{1j}\right)}.$$

In addition to the estimates computed through this statistical methodology, marginal effects for each of the variables are presented. The marginal effect of a predictor is defined as the partial derivative of the event probability with respect to the predictor of interest.[32] The marginal effect measurement is therefore very useful in order to interpret the effects of the regressors on the dependent variable for discrete dependent variable models, in this case, a logit binary choice model. Marginal effects are therefore mathematically expressed as follows below.

For simplicity, consider now the same model but with only one regressor. It is called logit because:

$$\Pr\left[Y_j = 1\middle|X_j\right] = F\left(\boldsymbol{\alpha}_0 + \boldsymbol{\beta}_0 X_j\right)$$

where X_j is the explanatory variable and $\boldsymbol{\alpha}_0$ and β_0 are unknown parameters to be estimated, and

$$F(x) = \frac{1}{1+\exp(-x)}$$

is the distribution function for the logistic (logit) distribution.

If $\beta_0 > 0$ then $\Pr[Y_j = 1|X_j] = F(\boldsymbol{\alpha}_0 + \beta_0 X_j)$ is an increasing function of X_j:

$$\frac{\partial P\left[Y_j = 1|X_j\right]}{\partial X_j} = \boldsymbol{\beta}_0 F'\left(\boldsymbol{\alpha}_0 + \boldsymbol{\beta}_0 X_j\right)$$

[32] For a formal definition and derivation, see Bierens (2008), on which the present study's estimation of marginal effects is based, and 'Usage Note 22604: Marginal effects estimation for predictors in logistic and probit models.' http://support.sas.com/kb/22/604.html, for a detailed empirical calculation of marginal effects.

where F' is the derivative of $F(x) = \frac{1}{1+\exp(-x)}$;

$$F'(x) = \frac{\exp(-x)}{(1+\exp(-x))^2} = \frac{1+\exp(-x)}{(1+\exp(-x))^2} - \frac{1}{(1+\exp(-x))^2}$$
$$= \frac{1}{1+\exp(-x)} - \frac{1}{(1+\exp(-x))^2} = F(x) - F(x)^2 = F(x)(1-F(x)).$$

Thus, the marginal effect of X_j on $\Pr[Y_j = 1|X_j]$ is dependent upon X_j:

$$\frac{\partial P\left[Y_j = 1|X_j\right]}{\partial X_j} = \boldsymbol{\beta}_0 F\left(\boldsymbol{\alpha}_0 + \boldsymbol{\beta}_0 X_j\right)\left(1 - F\left(\boldsymbol{\alpha}_0 + \boldsymbol{\beta}_0 X_j\right)\right).$$

The study reports the average marginal effects of each explanatory variable in the reported models and Tables 4–6 report summary statistics.

5. Analysis of results

Table 7 presents the results from logistic regressions of the financial distress indicator on the predictor variables. As required by the binary logistic regression model, firms classified as financially distressed were given a value of 1 and firms identified as financially healthy were given the value 0. This classification was carried out using the previously discussed financially-based definition of distress developed specifically for this analysis. The present study develops three main ex-ante models for estimating financial distress likelihood to test the contribution of macroeconomic indicators and market variables to the predictive accuracy of models based on financial statement ratios. Model 1 represents the 'Accounting only' model and incorporates the financial statement ratios Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE). Model 2 represents the 'Accounting plus macroeconomic indicators' model and includes, in addition to the accounting variables, the indicators Retail Price Index (RPI), and the Short Term Bill Rate adjusted for inflation (SHTBRDEF). Model 3 is the 'Full

Table 4
Summary statistics for Model 1.

Variable	TFOTL	TLTA	NOCREDINT	COVERAGE
Panel A: entire data set				
Mean	0.068572	0.486146	−0.121824	0.530676
Std. Dev.	0.338255	0.188591	0.986025	0.819871
Min	−1	−0.432123	−1	−1
Max	1	1	1	1
Observations	18,276			
Panel B: non-financially distressed firms				
Mean	0.089208	0.482734	−0.113742	0.593286
Std. Dev.	0.323753	0.183374	0.986886	0.77798
Min	−1	−0.432123	−1	−1
Max	1	1	1	1
Observations	17,349			
Panel C: financially distressed firms				
Mean	−0.317646	0.550002	−0.273086	−0.641079
Std. Dev.	0.370257	0.260108	0.95777	0.69207
Min	−1	−0.302382	−1	−1
Max	0.99792	1	1	1
Observations	927			

Notes: This table presents summary statistics for Model 1, which includes only financial statement variables. It covers the mean, standard deviation, minimum and maximum values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE). Panel A contains summary statistics for the entire data set; Panel B for financially healthy firms, and Panel C for firms in financial distress.

model' incorporating, in addition to the above financial statement ratios and macroeconomic indicators, four market variables: each firm's Equity Price (PRICE) transformed using the logarithmic function; the firm's cumulative monthly abnormal returns on an annual basis (ABNRET), generated as the firm's excess returns minus the FTSE All Share return index for the same period of time; the firm's relative size (SIZE) measured by the market capitalisation relative to the total size (market capitalisation) of the FTSE All Share index, in logarithmic form. Additionally, Model 4 and Model 5 are included in Table 7, representing a 'Market only' model and a 'Market plus macroeconomic variables' model, respectively, in order to compare their predictive accuracy with that of Model 1 and Model 2. The objective of this additional comparison is to test the predictive accuracy of accounting models against the performance of market models using logistic regression.

As mentioned above, the present study develops ex-ante models for the estimation of financial distress likelihood. In practice, the date of the event of financial distress is not known and risk managers are required to employ the data that is available at the time of the analysis in order to make an estimate of the likelihood of failure or financial distress of a company. Accordingly, this study estimates the probability of failure in the year prior to the observation of corporate financial distress ($t-1$) as well as two years prior to the financial distress event ($t-2$). In that way, the models provide evidence about the predictors that best discriminate between financially distressed and healthy companies on the one hand, and on the other, test their predictive power. Thus, for the $t-1$ models, all of the accounting ratios were computed using the financial statements of the year prior to the financial distress event. Accordingly, the macroeconomic indicators were calculated with information from the year preceding the distress event: the Retail Price Index (RPI) in base 100 as well as the 3-month Bill rate (SHTBRDEF), which was annualised and deflated using the inflation rate in order to obtain a measure of the level of 'real' interest rates in the economy. As for the market variables, equity prices (PRICE) were incorporated to the model as the official closing price in $t-1$, the variable measuring abnormal returns (ABNRET) for year t, when the distress event was observed, was calculated as the return of the firm in year $t-1$ minus the FTSE All Share Index return in year $t-1$. Individual firms' annual returns were generated by cumulating monthly returns. With regard to the variable that measures the relative size of the firm (SIZE), following Shumway (2001), individual firms' market capitalisation was measured at the end of the year before the financial distress event year.

Table 5
Summary statistics for Model 2.

Variable	TFOTL	TLTA	NOCREDINT	COVERAGE	RPI	SHTBRDEF
Panel A: entire data set						
Mean	0.067493	0.485921	−0.118042	0.525922	178.39851	2.048426
Std. Dev.	0.339813	0.189284	0.986466	0.822947	32.220261	2.427929
Min	−1	−0.432123	−1	−1	94.59	−4.69551
Max	1	1	1	1	235.18	7.7407
Observations	18,070					
Panel B: non-financially distressed firms						
Mean	0.088319	0.482455	−0.109658	0.589027	177.75165	2.068698
Std. Dev.	0.325357	0.184057	0.987328	0.781256	32.427066	2.442916
Min	−1	−0.432123	−1	−1	94.59	−4.69551
Max	1	1	1	1	235.18	7.7407
Observations	17,143					
Panel C: financially distressed firms						
Mean	−0.317646	0.550002	−0.273086	−0.641079	190.36081	1.673542
Std. Dev.	0.370257	0.260108	0.95777	0.69207	25.31356	2.097986
Min	−1	−0.302382	−1	−1	115.21	−4.69551
Max	0.99792	1	1	1	235.18	7.1745
Observations	927					

Notes: This table presents summary statistics for Model 2, which includes financial statement ratios as well as macroeconomic variables. It covers the mean, standard deviation, minimum and maximum values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), Interest Coverage (COVERAGE), the Retail Price Index (RPI), and the proxy for interest rates, the 3-month Short Term Bill rate adjusted for inflation (SHTBRDEF). Panel A contains summary statistics for the entire data set, Panel B for financially healthy firms, and Panel C for firms in financial distress.

Table 6
Summary statistics for Model 3.

Variable	TFOTL	TLTA	NOCREDINT	COVERAGE	RPI	SHTBRDEF	PRICE	ABNRET	SIZE	MCTD
Panel A: entire data set										
Mean	0.097363	0.497767	−0.19551	0.599672	178.08903	2.046149	4.427373	−0.108952	−10.046418	0.91036
Std. Dev.	0.27721	0.169538	0.973386	0.770045	32.874323	2.532696	1.702743	0.386299	2.22842	0.192053
Min	−1	−0.102771	−1	−1	94.59	−4.69551	−3.912023	−0.999988	−16.602146	0.002877
Max	1	1	1	1	235.18	7.7407	14.151983	0.999996	−2.374161	1
Observations	13,529									
Panel B: non-financially distressed firms										
Mean	0.118203	0.492827	−0.184269	0.669078	177.4168	2.066005	4.526808	−0.086315	−9.913979	0.919151
Std. Dev.	0.258451	0.163083	0.975489	0.713444	33.102993	2.553595	1.630117	0.374557	2.189381	0.17828
Min	−1	−0.102771	−1	−1	94.59	−4.69551	−3.912023	−0.999829	−16.480853	0.006411
Max	1	1	1	1	235.18	7.7407	14.151983	0.999996	−2.374161	1
Observations	12,801									
Panel C: financially distressed firms										
Mean	−0.269089	0.584634	−0.393164	−0.620747	189.90931	1.696996	2.678938	−0.506989	−12.375197	0.755794
Std. Dev.	0.334293	0.242075	0.91392	0.70417	25.859392	2.10305	1.982343	0.372911	1.506558	0.318516
Min	−1	0.028495	−1	−1	115.21	−4.69551	−3.912023	−0.999988	−16.602146	0.002877
Max	0.724547	1	1	1	235.18	7.1745	10.96388	0.949759	−5.641377	1
Observations	728									

Notes: This table presents summary statistics for the full model, or Model 3, which includes financial statement ratios, macroeconomic indicators and market variables. It covers the mean, standard deviation, minimum and maximum values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), Interest Coverage (COVERAGE), the Retail Price Index (RPI), and a proxy for interest rates, the 3-month Short Term Bill Rate adjusted for inflation (SHTBRDEF), the firm's Equity Price (PRICE), the firm's annual Abnormal Returns (ABNRET), the firm's Relative Size (SIZE), and the ratio Market Capital to Total Debt (MCTD). Panel A contains summary statistics for the entire data set, Panel B for financially healthy firms, and Panel C for firms in financial distress.

Finally, as for the ratio Market Capitalisation to Total Debt (MCTD), the latter was also measured with information taken from financial statements issued in $t-1$.

Table 7 reports the resulting estimates from logistic regressions of the financial distress indicator on the independent variables. All of the variables in the 'accounting' model (Model 1) are statistically significant at 5–1% in $t-1$, which suggest that they are efficient predictors of the probability of financial distress. In $t-2$, or two years before the financial distress event was observed, all of the regressors retain their statistical significance except the accounting ratio Total Liabilities to Total Assets, which becomes statistically insignificant. This is the case not only for the 'accounting' model, but also for the 'accounting plus macroeconomic' model and the 'full' model.[33] The fact that all of the variables in Model 1 except one retain the same level of significance in both $t-1$ and $t-2$ suggest that the financial statement ratios that were retained in the model possess a high discriminating and predicting power. Furthermore, the coefficient estimates' signs possess the predicted sign: a negative sign of the ratio TFOTL, which represents a measure of the performance of a company, suggests that the higher the level of funds from operations a company produces (relative to their liabilities) the higher its performance and therefore the lower its probability of entering financial distress. Similarly, the sign of the variable NOCREDINT suggest that the higher the liquidity of a company,[34] the lower its financial distress likelihood. The COVERAGE variable also displays the anticipated negative sign, where an increased or substantial ability to pay interest on outstanding debt, lowers the firm's financial distress likelihood. The coefficient's estimate for the variable TLTA displays a positive sign which indicates, opposite to the previous accounting ratios, that a highly leveraged company (a high value of the TLTA variable) will display a higher likelihood of financial distress. This last result is also consistent with the present study's initial predictions. Interestingly, the COVERAGE coefficient estimate possesses the highest absolute value among the financial statement ratios, followed by TLTA and TFOTL, NOCREDINT having the smallest value. The same applies for the model estimated in $t-2$, which suggests that the accounting ratios' coefficient estimates are stable over the two periods of time.

Table 7 also presents Cox and Snell's R-squared as well as Nagelkerke's max rescaled R squared in order to have a comparison point of the *relative* increase or decrease in performance between models. As expected, the Nagelkerke's max rescaled R-squared decreases for Model 1 when it is estimated from $t-1$ to $t-2$. However, the magnitude of the decline is only marginal, which suggests that the models' regressors are stable over time. Nevertheless, these measures are only included to make comparisons easier and their interpretation needs to be treated with caution, as they do not have the same meaning for logit regressions as they have for ordinary least squares regressions. As previously discussed, a more appropriate and direct measure of the real performance of a logit model is the Area Under the Receiver Operating Characteristics Curve[35] (AUC), whose output will be discussed in the following lines.

Model 2, in addition to the accounting ratios, incorporates two macroeconomic indicators. Both of them, RPI and SHTBRDEF are statistically significant at 5–1% in the model estimated in $t-1$, and retain the same statistical significance in $t-2$, which indicate, as in the case of three out of four of the financial statement ratios, that the variables are stable over two periods. Furthermore, all of the variables initially included in Model 1 retain their statistical significance and the

[33] In the remainder of the present study the term 'Model 1' will be used to make reference to the 'Accounting' only model, 'Model 2' to the model that includes macroeconomic indicators in addition to financial statement ratios, and the term 'Model 3' will be representing the 'full model,' or the model that includes financial statement ratios, macroeconomic indicators and market variables. In addition 'Model 4' and 'Model 5' will be used to make reference to a 'Market only' model and a 'Market plus macroeconomic indicators,' respectively.

[34] Or, in the specific case of the No Credit Interval variable, the period that a company could finance its own business expenses, at its current level of activity, by drawing on its own liquid resources and on the assumption that it made no further sales.

[35] In the remainder of the present study, the Area Under the Receiver Operating Characteristics Curve will be referred to as 'AUC.'

Table 7
Logit regression of financial distress indicator on predictor variables.

Variable	Model 1		Model 2		Model 3		Model 4	Model 5
	$t-1$	$t-2$	$t-1$	$t-2$	$t-1$	$t-2$	$t-1$	$t-1$
TFOTL	−0.8105 **	−0.7327**	−0.7711**	−0.7357**	−1.0784**	−1.0001**		
	(6.74)	(6.18)	(6.30)	(6.19)	(6.51)	(6.26)		
TLTA	1.2825**	0.2048	1.3438**	0.2593	0.6102**	0.00600		
	(7.61)	(1.18)	(7.96)	(1.49)	(2.66)	(0.03)		
NOCREDINT	−0.2130**	−0.1670**	−0.2245**	−0.1685**	−0.1513**	−0.0938*		
	(4.80)	(3.79)	(5.07)	(3.81)	(2.83)	(1.82)		
COVERAGE	−1.3362**	−1.2792**	−1.2851**	−1.2481**	−0.9738**	−0.9678**		
	(22.99)	(22.36)	(22.00)	(21.56)	(14.24)	(14.21)		
RPI			0.0201**	0.0145**	0.0119**	0.00728**		0.0113**
			(8.45)	(5.85)	(4.27)	(2.60)		(4.57)
SHTBRDEF			0.1901**	0.2111**	0.1262**	0.1028**		0.1010**
			(6.51)	(5.63)	(3.84)	(2.45)		(3.48)
PRICE					−0.1043**	−0.0711**	−0.1716**	−0.1629**
					(4.00)	(2.79)	(6.92)	(6.49)
ABNRET					−1.1429**	−1.6046**	−1.7637**	−1.7378**
					(9.55)	(13.59)	(15.42)	(15.15)
SIZE					−0.2356**	−0.0440	−0.4398**	−0.4140**
					(7.23)	(1.47)	(15.49)	(14.43)
MCTD					−1.2944**	−0.6249**	−0.9757**	−1.0043**
					(7.53)	(3.16)	(6.97)	(7.13)
Constant	−7.8570**	−2.9831**	−7.8570**	−6.1015**	−7.2547**	−4.4563**	−6.9068**	−8.8751**
	(37.63)	(30.63)	(15.60)	(11.40)	(10.52)	(6.08)	(16.55)	(14.17)
Pseudo R^2	0.0926	0.0929	0.0965	0.0953	0.1420	0.1260	0.1017	0.1032
Max-resc R^2	0.2802	0.2626	0.2901	0.2674	0.4148	0.3527	0.2967	0.2984

Notes: This table reports results from logit regressions of the financial distress indicator on the predictor variables. The models were computed for two periods: using the accounts, market, and macroeconomic data from the year prior to the observation of the financial distress event ($t-1$), and the accounts, market, and macroeconomic data from two years prior to the observation of the financial distress event ($t-2$) in order to confirm their predictive ability in addition to their discriminating power. Additionally results are presented for a 'Market' model that incorporates market variables in $t-1$ for comparison purposes. The absolute value of Z-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%–1%.

relative magnitude of their coefficient estimates in Model 2. The signs of both indicators are also as predicted in the present study: the positive sign of the RPI variable's estimate indicates that a higher level entails an increased likelihood of financial distress. And the positive sign of the SHTBRDEF suggests that in a macroeconomic environment characterised by a high level of the real rate of interest, all other thing beings equal, the probability of financial distress for industrial firms increases. However, both macroeconomic regressors' estimates are lower in magnitude than the accounting ratios, RPI having the smallest estimate in absolute terms, which might suggest a smaller effect of the macroeconomic variables on the likelihood of firms' financial distress. With regard to the macroeconomic variables' contribution to the predictive accuracy of the accounting model, as directly measured by the AUC, it can be concluded that they contribute positively, although rather marginally, when the model is estimated in $t-1$: The AUC shows an increase from 0.87 to 0.88. However, when the model is estimated in $t-2$, the contribution of the macroeconomic indicators is less conclusive: a very small decrease is even observed from an AUC of 0.8523 to 0.8514, suggesting that in $t-2$, financial statement ratios alone are more powerful to predict financial distress than mixed with macroeconomic indicators.

Model 3 in Table 7 presents the results from logit regressions of the financial distress indicator on the accounting and macroeconomic predictor variables included in Model 2 plus 4 market variables: firms' stock prices, past abnormal returns, the relative size of the company and the ratio market capitalisation to total debt. All of the market variables that entered Model 3 are statistically significant at 5–1% when estimated in period $t-1$. With the notable exception of the SIZE, all of the variables retain the same levels of significance when estimated in $t-2$, suggesting that PRICE, ABNRET, and MCTD are powerful and consistent predictors over time of the likelihood of financial distress. SIZE was kept in the models as, in spite of its lack of statistical significance in $t-2$, it contributed positively to the predictive accuracy of the model as measured by the AUC. The only exception is NOCREDINT, which experienced a marginal decrease, from being statistically significant at 5–1% to 10% in the models estimated with data generated two years prior to the observation of the financial distress event. It should be also noted that the accounting ratio TLTA displays the same behaviour as in the previous analysis of Model 1 and Model 2; when Model 3 is estimated in period $t-1$ the ratio is significant at 5–1%, however, when it is estimated in period $t-2$, it ceases to be statistically significant, which suggests that TLTA, despite having a positive contribution to the predictive accuracy of the model, is not consistent over time. As for the signs of the coefficient estimates, they all are as predicted in this study: a negative sign of the PRICE variable indicates that there is a negative relationship between stock price levels and the likelihood of financial distress of public companies, as market prices reflect investors' expectations of future cash flows or earnings, and the company's earnings are affected by its financial position. The sign of the ABNRET's estimate, suggest that, as posited, there is a negative relationship between this regressor and the probability of financial distress. Investors do seem to discount the equity of those firms that are in a stressed financial position or close to default/bankruptcy, and the returns of the company seem to be affected in consequence: individual returns of a company outperforming the returns of the FTSE All Share Index are a sign of good financial health and thus decrease the likelihood of financial distress. Contrarily, company's returns that fall short to match the FTSE All Share Index's returns (negative returns) are a consistent predictor of financial distress over time (both in $t-1$ and $t-2$). The sign of MCTD suggests a negative relationship between this variable and the probability of financial distress. The study expected this ratio to enhance the predictive accuracy of the model and to be consistent over time as it was constructed to include, on the one hand, a market approach (through the measure of market capitalisation) and, on the other, to solve the problem highlighted

Table 8
Model performance measures.

Measure	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A: models' performance in $t-1$					
AUC	0.8718	0.8763	0.9190	0.8712	0.8727
Gini rank coefficient	0.7436	0.7526	0.8380	0.7424	0.7454
Kolmogorov–Smirnov	0.5949	0.6021	0.6704	0.5939	0.5963
Cox & Snell's R^2	0.0926	0.0965	0.1420	0.1017	0.1032
Nagelkerke's R^2	0.2802	0.2901	0.4148	0.2967	0.2984
χ^{2a} (4, 6, 10, 4, 6)	1776.13 ($p < .0001$)	1834.72 ($p < .0001$)	2072.44 ($p < .0001$)	1587.72 ($p < .0001$)	1588.23 ($p < .0001$)
Hosmer & Lemeshow goodness-of-fit test					
χ^2 (8)	86.5081	55.8609	10.2224	12.5565	18.5788
Pr > χ^2	<.0001	<.0001	0.2498	0.1280	0.0173
Panel B: models' performance in $t-2$					
AUC	0.8523	0.8514	0.8918	0.8355	0.8358
Gini rank coefficient	0.7046	0.7028	0.7836	0.6710	0.6716
Kolmogorov–Smirnov	0.5637	0.5622	0.6269	0.5368	0.5373
Cox & Snell's R^2	0.0929	0.0953	0.1260	0.0822	0.0831
Nagelkerke's R^2	0.2626	0.2674	0.3527	0.2302	0.2301
χ^{2a} (4, 6, 10, 4, 6)	1550.94 ($p < .0001$)	1573.33 ($p < .0001$)	1657.38 ($p < .0001$)	1167.70 ($p < .0001$)	1158.12 ($p < .0001$)
Hosmer & Lemeshow goodness-of-fit test					
χ^2 (8)	97.7438	45.3124	13.7421	10.7357	18.1839
Pr > χ^2	<.0001	<.0001	0.0887	0.2171	0.0199

Notes: This table reports model performance statistics. Panel A shows measures for the five models estimated in period $t-1$ and Panel B displays the same measures for all of the models estimated in $t-2$. Model 1 is the 'accounting only' model, Model 2 is the 'accounting plus macroeconomic variables' model, Model 3 if the 'full' model, including market variables in addition to the variables in Model 2, Model 4 is the 'market only' model, and Model 5 is the 'market plus macroeconomic variables' model. The first measure is a direct measure of the predictive accuracy of models estimated using the logit methodology, the Area Under the Receiver Operating Characteristics Curve (AUC); Gini coefficients, Kolmogorov–Smirnov statistics, Cox and Snell *R*-squared, Nagelkerke's Max-rescaled *R*-squared and the models' Chi-square are also presented. Additionally, Hosmer and Lemeshow goodness-of-fit statistics are displayed.

[a] The parenthesis following the models' χ^2 represent the degrees of freedom for each estimated model: 4 for Model 1, 6 for Model 2, 10 for Model 3, 4 for Model 4, and 6 for Model 5.

in Beaver et al. (2005), namely that the variables ABNRET and SIZE are not scaled in that they are not compared to the magnitude of debt outstanding. By including total debt as denominator, it solves this problem without giving rise to multicollinearity problems with the variable SIZE. As expected, this is a powerful as well as consistent predictor of financial distress over time. The sign of the market variable SIZE is also as predicted: companies with a high level of SIZE (high market capitalisation relative to the FTSE All Share market capitalisation) are more stable (and/or well established), indicating a good level of the debt holders 'equity cushion,' far from the 'strike price' (or the value of liabilities), and therefore judged by investors as capable of serving their debt obligations, lowering thus the likelihood of financial distress. As to the magnitude of the coefficients' estimates, ABNRET possesses the highest absolute value in Model 3, estimated in $t-1$ as well as $t-2$, followed by MCTD in $t-1$ but not in $t-2$, where it displays a lower absolute magnitude, followed by SIZE and PRICE. It is therefore concluded that the market variables are also consistent predictors of the likelihood of financial distress over time.

Table 8 presents the model performance statistics for the five models estimated in both $t-1$ and $t-2$. The Area Under the ROC Curve (AUC) is a direct and appropriate measure of the predictive accuracy of models developed using the logit methodology. DeLong, DeLong, and Clarke-Pearson (1988) state that 'when a test is based on an observed variable that lies on a continuous or graded scale, an assessment of the overall value of the test can be made through the use of a receiver operating characteristic (ROC) curve.'[36] Furthermore, Altman et al. (2010) argue that 'The ROC curve plots the true positive against the false positive rate as the threshold to discriminate between failed and non-failed firms' changes. The Area Under the ROC Curve is a measure of the predictive accuracy of the model, with a value of 1 representing a perfect model.' Gini rank correlation coefficients[37] and Kolmogorov–Smirnov statistics, also present in Table 8, are widely used analysis tools by scoring analysts to assess the predictive accuracy of in-sample and hold-out tests (Altman et al., 2010). The advantage of these tests is that they are easy to interpret and calculate, as both can be derived from the AUC. As Anderson (2007) argues, the Gini rank coefficient has been co-opted by credit scoring analysts, who employ it as a measure of 'how well a scorecard is able to distinguish between goods and bads' where 'the end result is a value representing the area under the curve.' The Gini coefficient is very similar to the AUC, the difference is that the former calculates only the area between the curve and the diagonal of the Lorenz curve, unlike the latter, which calculates the full area below the curve.[38] As a reference point, in the context of professional credit scoring analysis, a Gini coefficient equal to or above 50% is a very satisfactory level in a retail environment, as discussed by Anderson (2007). In the context of the present study, the Gini rank coefficient is used in order to complement and check the consistency of the other measures presented.

The Kolmogorov–Smirnov test is performed to measure the maximum vertical deviation between two empirical cumulative distribution functions (good and bad) in credit score modelling. This measure is, according to Anderson (2007) and Mays (2004), 'the most widely used statistic within the United States for measuring the predictive power of rating systems.'[39] However, Anderson (2007) recommends not using this statistic (or any other measure of the predictive accuracy of a model) in isolation, but rather as a complement to others such as the AUC or the Gini rank coefficient, which is the approach adopted in the present study. Mays (2004) suggest that the acceptable values for this statistic range from 20% to 70%, above which the model is 'probably too good to be true.' Cox and Snell's *R*-squared is a measure based on the

[36] p. 837.

[37] The Gini rank correlation coefficient can be found as the Somer's D statistic in the SAS software and most statistical software packages.

[38] As such, it can be computed as $((2 * \text{AUC}) - 1)$ following Altman et al. (2010).

[39] Anderson (2007, p. 196).

log-likelihood of the model, the log-likelihood of the original (baseline) model and the sample size, and Nagelkerke's Max-rescaled R-squared is a refinement of the former. In other words, both can be considered as measuring the same concept. In general, they can also be interpreted very similarly (but not identically), to the R-squared in linear regression, as they are measures of the significance of the model.[40] The Hosmer and Lemeshow goodness-of-fit test for binary response logistic models is also provided. As discussed by Ragavan (2008), the subjects are divided into approximately ten groups of roughly the same size based on the percentiles of the estimated probabilities. The discrepancies between the observed and expected number of observations in these groups are summarised by the Pearson chi-square statistic, which is then compared to a chi-square distribution with k degrees of freedom, were k is the number of groups (10) minus n (2).[41] Thus, a small chi-square (<15) and a large p-value (>0.05) should suggest that the model is effective to predict the behaviour of the data, or that the fitted model is an appropriate one to be employed in order to predict the specified binary outcomes in the dataset.

Table 8 shows the performance of all of the models in the study. From the results presented in Panel A, which correspond to the models estimated in period $t-1$, it can be concluded that even if Model 1, the 'accounting only' model, possesses an already high discriminating accuracy as measured by the AUC, the addition of macroeconomic indicators and market variables can contribute positively and substantially to the performance of the financial distress prediction models. Furthermore, it is demonstrated that a distress prediction model, does not require the inclusion of a large number of regressors (as in some previous academic studies) to display a high discriminating and predictive accuracy; in the present study, a set of only 10 regressors yielded an impressive AUC of 0.92 in period $t-1$ (which decreased only marginally to 0.89 in period $t-2$), suggesting that the independent variables retained in the model act as complementary and not as substitutes (or mutually exclusive). It is also important to highlight the fact that the high discriminating and predictive accuracy of the full model in the present study might be explained by the specific combination of independent variables, which were selected taking into consideration the problems highlighted in previous research work with regard to the representation of the main, most likely, and potential indicators of financial distress. A very large number of financial ratios, macroeconomic indicators and market variables were tested. Redundant variables were discarded, indicators that have proven their contribution to the performance of the models in previous research were included, and potentially useful new ones were tested. An example of a new indicator that had not yet been tested is the ratio market capitalisation to total debt (MCTD), which proved to contain information useful to the prediction of financial distress. The result was a new distress prediction model with a new set or combination of variables for quoted companies in the United Kingdom that proved to be very well positioned relative to previous and well-known models for the prediction of company's default/distress.[42]

From Model 1 to Model 2 in period $t-1$, an increase in the performance of the models measured by the AUC was observed (from 0.872 to 0.876), which indicates that macroeconomic variables contribute only marginally, though positively, to the predictive accuracy of a model based on financial statement ratios. As the Gini rank coefficient and the Kolmogorov–Smirnov statistic are both derived from computations based on the level of the AUC, they follow the same pattern as the latter, and fall into the (previously discussed) highest ranges that are considered by credit scoring professionals as acceptable. On the other hand, a considerable increase in the AUC is observed when market variables are added in Model 3 (from an AUC equal to 0.88 to an AUC equal to 0.92); the magnitude of the enhancement suggest that market variables contain a substantial amount of information that is not available in financial statements but that was taken into consideration by the markets and act as a complement to the information provided by accounting ratios.[43] Furthermore, the present study also estimates Model 4 and Model 5 in order to directly compare the performance of the 'accounting only' model (Model 1) and the 'accounting plus macroeconomic variables' model (Model 2) against the 'market only' model (Model 4) and the 'market plus macroeconomic variables' model (Model 5) respectively. It can be observed that accounting and market models in isolation yield almost the same predictive accuracy, with an AUC of 0.8718 and 0.8712 for the accounting and market only models respectively, and an AUC of 0.8763 and 0.8727 when macroeconomic variables are added to the models. In both cases, the inclusion of macroeconomic variables enhances, although marginally, the predictive accuracy. The accounting models have a marginally better performance when estimated in period $t-1$ using binary logistic regression as the main statistical methodology. It is therefore of paramount importance to highlight the prominent increase in predictive accuracy (from an AUC equal to 0.88 to 0.92) resulting from the combination of two models that yield an almost equal (both significantly minor to the 'full model') predictive accuracy when they are estimated in isolation.

Table 8 also presents the results of Hosmer and Lemeshow goodness-of-fit tests. Despite the different results obtained in previous research works, and the controversy surrounding its consistency, the present study reports the results of the goodness-of-fit test as it points to an interesting observation worth taking into consideration: when Model 1 and Model 2 (the 'accounting only' model and the 'accounting plus macroeconomic variables' model respectively) are estimated, the Hosmer and Lemeshow goodness-of-fit test show a large chi-square and a p-value < .0001, both of which indicate that the model, although displaying a high predictive accuracy, might lack other independent variables that are capital in order to explain a higher proportion of the phenomenon that a model is trying to elucidate. On the other hand, it can be observed that the opposite is true when market variables are incorporated to the 'accounting and macroeconomic variables model' in Model 3: the results for the Hosmer and Lemeshow goodness-of-fit test show a small chi-square (<15) and a large p-value (>0.05) that suggests that Model 3 is and adequate model. In other words, these values imply that the model fitted with market variables is more appropriate to predict the data (to better discriminate and predict the specified binary outcomes in the dataset: healthy from financially distressed companies). This argument finds additional support in the significantly larger AUC (from 0.88 to 0.92) when market variables are present. In order to test if the same results hold true for models based on market variables, the same test was applied to Model 4 and Model 5 (the 'market only' model and the 'market plus macroeconomic variables' respectively). Consistent with the previous analysis of results, Model 4 displays a chi-square with a value below 15 and a p-value well above the 0.05 threshold, suggesting that market variables are appropriate regressors to measure the likelihood of financial distress. Interestingly, when macroeconomic indicators are added to the 'market only' model, both Hosmer and Lemeshow goodness-of-fit statistics display better

[40] See Cox and Snell (1989) and Nagelkerke (1991).

[41] p. 10.

[42] With the advantages of accuracy, simplicity and timeliness.

[43] An example of the information that is not included in financial statements (as by nature they contain only past information), might be the information regarding the future prospects of a firm such as an insufficient level of Research and Development expenditure, or the negative forecast for a specific industry due to industry-specific micro or macroeconomic developments taking place. Information of this kind is typically taken into account by investors and market participants in their analysis and is therefore reflected by market variables only such as equity prices or firms' returns.

values than for the accounting models (Model 1 and Model 2). Furthermore, the same results apply for the models estimated in $t-2$, making the above interpretation more consistent.

Unsurprisingly, the predictive accuracy of the models estimated in $t-2$ experiences a decrease, which is consistent with previous default prediction models. However, the same patterns can be observed when financial statement ratios, macroeconomic indicators and market variables are combined in a single model. The only exception that can be observed is between Model 1 and Model 2; when macroeconomic variables are added to the 'accounting only' model, there is a marginal decrease in predictive accuracy (from and AUC of 0.852 to an AUC of 0.851), suggesting that financial statement ratios are (marginally) more reliable regressors than macroeconomic indicators when the likelihood of financial distress is estimated in $t-2$. Nevertheless, because of the inconsequential (very small) decrease in performance, it could also be argued that the predictive accuracy remains unchanged when macroeconomic indicators are included in an accounting model estimated in $t-2$. As to Model 3, it can be concluded that the addition of market variables to Model 2 (estimated in $t-2$) increases considerable the predictive accuracy by the same magnitude as when it was estimated in period $t-1$: from an AUC of 0.851 to 0.892. Model 5 also shows an increase in predictive accuracy relative to Model 4: from an AUC of 0.835 to 0.836, suggesting that, although marginally, macroeconomic variables contribute positively to the performance of the model. However, as in the case of Model 1 and Model 2, the contribution is so small that the performance could also be considered as unchanged. Again, this analysis confirms the consistency of the behaviour of macroeconomic indicators when added either to the $t-2$ 'accounting only' model or to the 'market only' model. The additional Gini rank coefficients as well as the Kolmogorov–Smirnov tests display patterns consistent with the above discussion and confirm the previous results, both the models estimated in $t-1$ and the ones estimated in $t-2$. Moreover, the predictive accuracy of the models presented in this study can be located in the high end of the ranges specified by professional credit managers when measured through the Gini coefficient and the Kolmogorov–Smirnov statistic.

As stated by Cleves (2002), 'occasionally, there is a need to compare the predictive accuracy of several fitted logit (logistic) or probit models by comparing the areas under the corresponding receiver operating characteristic (ROC) curves.'[44] In order to perform the comparisons, the present study applies for the first time, in financial distress prediction models, a methodology based on a non-parametric approach that employs the theory developed for generalised Mann–Whitney *U*-statistics. The present study follows the methodology presented in DeLong et al. (1988) and takes thus into account the correlated nature of the data that arises when two or more empirical curves are constructed using tests performed on a same set of firms. This issue is paramount as most of the comparisons of ROC curves made in previous studies, not only in the field of finance but also in fields such as atmospheric science and medical diagnosis, for which predictions of specific outcomes are essential, employ the already available computations in most statistical analysis software packages. The problem with this approach is that the models to be compared (derived using the same dataset) are estimated on the same number or set of observations. For instance, as highlighted by Cleves (2002), when the commands 'roccontrast' in SAS or 'roccomp' in Stata are employed to compare the curves after running the logistic procedure, the programs use the same number of observations for all models, as they drop from the computation any observation[45] in which at least one of the covariate values is missing (which varies between models). Therefore, difficulties can arise if there are missing values included in some models but not in others, as the exclusion of valid observations that would have otherwise been used in the normal estimation of the logit model, lead to inconsistent and erroneous computations of the Area Under the Receiver Operating Characteristics Curve.

The comparison of curves in the present study takes into account the correlated nature of the data,[46] on the one hand, and solves the problem of comparison of two or more models using a constant number of observations, on the other. Following DeLong et al. (1988) and combining the use of the SAS logistic statistical methodology with the ROC macros available from the SAS Institute,[47] the present paper reports a useful visual comparison of the differences in predictive accuracy of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model and the 'full' model using a non-parametric approach based on the theory on generalised Mann–Whitney *U*-statistics. The graphic is constructed plotting the models' ability to identify true positives (sensitivity), on the Y axis, and its ability to detect true negatives ($1-$ specificity). In other words, each individual ROC curve is generated (in the field of financial distress prediction models) by plotting the proportion of true distressed companies out of the companies classified by the model as distressed ('True Positive Rate') against the proportion of false distressed companies (healthy companies) out of the companies classified by the model as distressed ('False Positive Rate') at various cutpoints. As to the use and interpretation of the plots' results, 'if a test could perfectly discriminate, it would have a value above which the entire abnormal population would fall and below which all normal values would fall (or vice versa). The curve would then pass through the point (0, 1) on the unit grid. The closer a ROC curve comes to this ideal point, the better its discriminating ability. A test with no discriminating ability will produce a curve that follows diagonal of the grid.'[48] Additionally, the areas under the receiver operating characteristic curve of the three fitted models are tested for equality, where an overall p-value below 0.05 is indicative of differences between the areas. In other words, an overall p-value <0.05 signifies that the null hypothesis of equality of areas under the ROC curve can be rejected, thus confirming the reliability of the results.

The nonparametric comparison of the areas under correlated ROC based on the theory developed for generalised Mann–Whitney *U*-statistics was performed, initially, on 3 models estimated in period $t-1$: the 'accounting' model, the 'accounting plus macroeconomic variables' model, and the 'full' model that includes market variables. Then, two out of the three models with the best predictive accuracy, based on the Area Under the ROC Curve, were selected for another comparative test with the aim of graphically presenting the increase in predictive accuracy when market variables are added to Model 2, on the one hand, and to test whether the AUC is differs statistically between the two models, on the other. Furthermore, the above procedure for the three models estimated in $t-1$ was repeated for the same three models estimated in $t-2$. The present study presents thus 4 figures that allow a comparison between models and between estimation periods that facilitates the analysis of the differences in predictive accuracy as well as the contribution of the different sets of variables (financial statement ratios, macroeconomic indicators, and market variables) over time. Figs. 1 to 4 show a graphic representation of the discussion drawn from Table 7, regarding the differences in the predictive accuracy of the models through the interpretation of their respective AUCs: it can be thus confirmed

[44] p. 301.

[45] Stata's 'roccomp' command also drops from the computation any observation in which at least one of the predicted probabilities is missing. See Cleves (2002).

[46] The implicit correlation between the curves when two or more empirical curves are constructed using tests performed on a same set of firms.

[47] The use of the SAS PROC LOGISTIC and the macros available from the SAS Institute results in a method capable of comparing each model's receiver operating characteristics area computed using the entire available number of observations specific to each individual model and not a constant number of observations for all models, thus avoiding the problem highlighted by Cleves (2002).

[48] DeLong et al. (1988, p. 837).

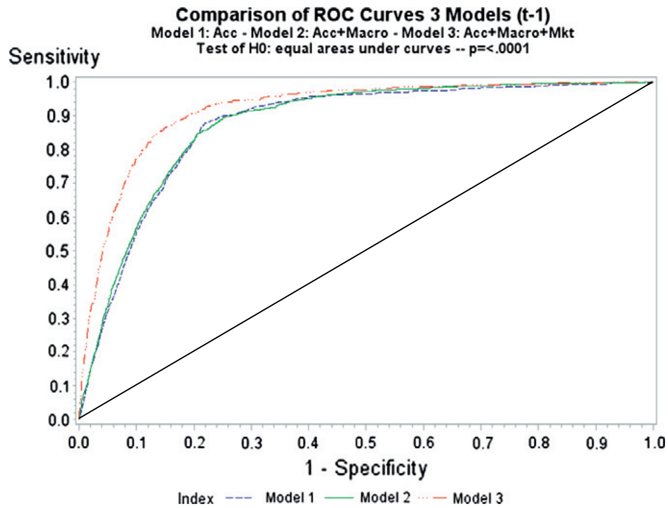


Fig. 1. Comparison of areas under the receiver operating characteristic curve of Model 1, Model 2, and Model 3 estimated in period $t-1$. The figure plots the AUC of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model and the 'full model,' including market variables; Model 1, Model 2, and Model 3 respectively, estimated in period $t-1$. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 1 AUC = 0.87, Model 2 AUC = 0.88, and Model 3 AUC = 0.92. The discriminating accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly discriminate the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its discriminating ability. The overall p-value = <0.0001 indicates that the null hypothesis of equality of areas under the ROC curve can be rejected. In other words, the small p-value of this test strongly suggests that the three areas differ statistically.

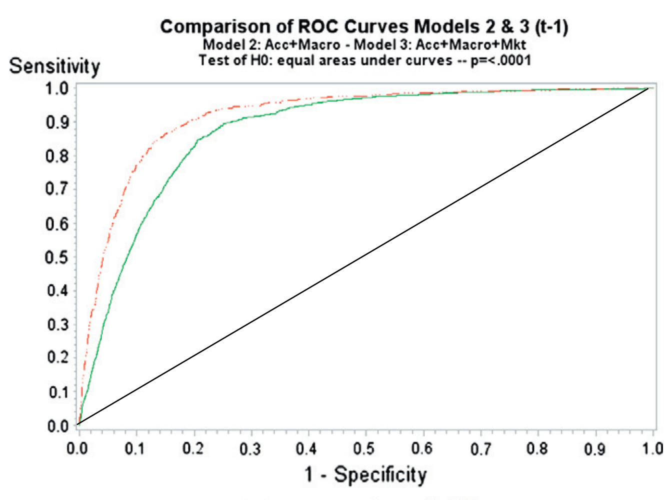


Fig. 2. Comparison of areas under the receiver operating characteristic curve of Model 2, and Model 3 estimated in period $t-1$. The figure plots the AUC of the two models with the best discriminating ability: Model 2 and Model 3 estimated in period $t-1$, the 'accounting plus macroeconomic indicators' model and the 'full model,' including market variables, respectively. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 2 AUC = 0.88, and Model 3 AUC = 0.92. The discriminating accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly discriminate the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its discriminating ability. Similar to the above comparison of the three models, the overall p-value = <0.0001 indicates that the null hypothesis of equality of areas under the ROC curve for Model 2 and Model 3 can be rejected. In other words, the small p-value of this test strongly suggests that the three areas differ statistically.

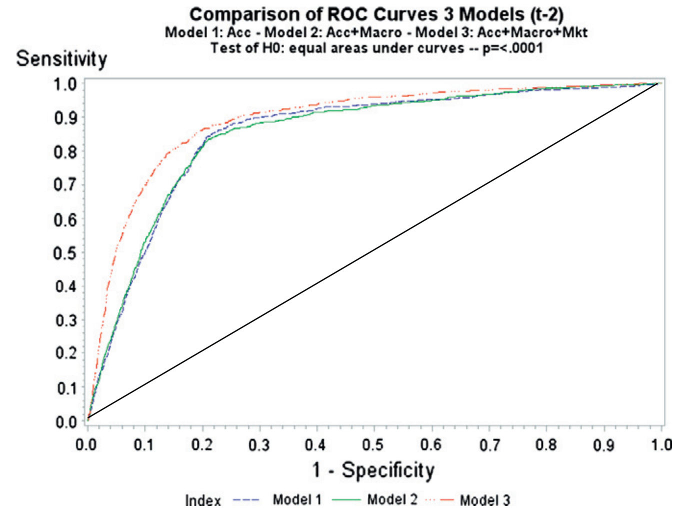


Fig. 3. Comparison of areas under the receiver operating characteristic curve of Model 1, Model 2, and Model 3 estimated in period $t-2$. The figure plots the AUC of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model and the 'full model,' including market variables; Model 1, Model 2, and Model 3 respectively, estimated in period $t-2$. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 1 AUC = 0.85, Model 2 AUC = 0.85, and Model 3 AUC = 0.89. The predictive accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly predict the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its predicting ability. The overall p-value = <0.0001 indicates that the null hypothesis of equality of areas under the ROC curve can be rejected. In other words, the small p-value of this test strongly suggests that the three areas differ statistically.

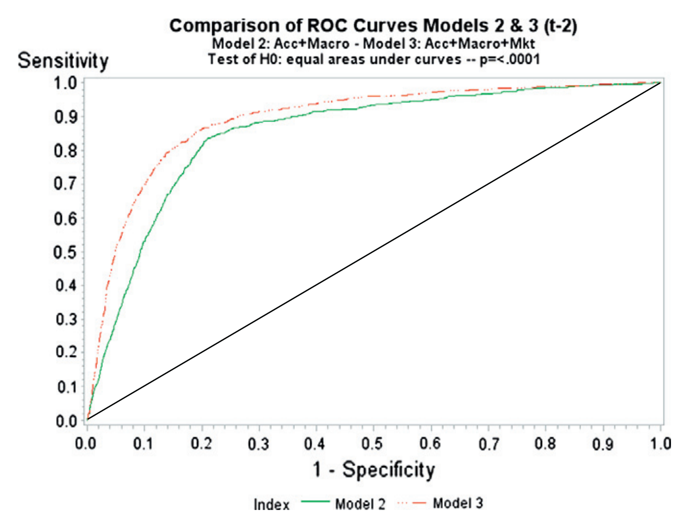


Fig. 4. Comparison of areas under the receiver operating characteristic curve of Model 2, and Model 3 estimated in period $t-2$. The figure plots the AUC of the two models with the best predictive ability: Model 2 and Model 3 estimated in period $t-2$, the 'accounting plus macroeconomic indicators' model and the 'full model,' including market variables, respectively. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 2 AUC = 0.85, and Model 3 AUC = 0.89. The predictive accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly predict the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its predictive ability. Similar to the above comparison of the three models, the overall p-value = <0.0001 indicates that the null hypothesis of equality of areas under the ROC curve for Model 2 and Model 3 can be rejected. In other words, the small p-value of this test strongly suggests that the three areas differ statistically.

that the contribution of macroeconomic indicators to the performance of the accounting model is positive, though marginal, when the model is estimated in $t-1$, however, results are less conclusive when the model is estimated in $t-2$: there is even a very small decrease in performance entailed by the inclusion of macroeconomic indicators. It can be therefore concluded that financial statement ratios are more powerful to predict financial distress in period $t-2$. On the other hand, the inclusion of market variables results in a substantial increase in the predictive accuracy of 'accounting plus macroeconomic indicators' models, showing consistency when they are estimated in both periods $t-1$ and $t-2$. Finally, it is worth noting that the four comparisons of areas under the curve show an overall p-value $= <0.0001$ which indicates that the null hypothesis (H0) of equality of areas under the ROC curve can be rejected. In other words, the small p-value of the resulting from the test strongly suggests that the three areas differ statistically and that the analysis is reliable.

5.1. Marginal effects and changes in predicted probabilities

The parameters estimated from binary response models, unlike those estimated by linear models, cannot be directly interpreted because they do not provide useful information that fully describes the relationship between the independent variable and the outcome (Long & Freese, 2003). Previous bankruptcy, default, and financial distress prediction models constructed using binary response models invariably focus only on the overall discriminating or predictive accuracy of the models presented and very rarely do they provide an interpretation of the relationship between the predictor variables and the binary outcome. Such studies report solely the estimates obtained from binary response models and provide an interpretation of the direction of the relationship based on the sign of the estimate. Nevertheless, the basic output (the coefficient estimates) obtained by performing binary response models cannot explain the effects of individual variables on the model's outcomes because of their nonlinear nature. Marginal effects and predicted probabilities are appropriate analytic tools to treat this issue.

This section presents results of the computation of marginal effects of individual regressors as well as graphic representations of predicted probabilities of financial distressed companies. This section intends to fill an important gap in the default/financial distress prediction models literature, where the measurement of expected instantaneous changes in the response variable (financial distress indicator in the present study) as function of a change in a specific predictor variable while keeping all the other covariates constant, has been overlooked. As previously discussed, marginal effect measurements (defined as the computation of the partial derivative of the event probability with respect to the predictor if interest) are very useful to the interpretation of the individual effects of the regressors on the dependent variable in discrete dependent variable models, or binary response models (logit regression in the present study). With regard to their calculation, the present study's methodology consists of outputting the marginal effects estimated at each observation in the dataset and then computing the sample average of individual marginal effects in order to obtain the overall marginal effects. SAS statistical software code was employed to generate the estimated marginal effects. Predicted probabilities were generated by plotting the vector reflecting the variations in the predicted probability of financial distress (the predicted probability that the financial distress indicator, Financial_Distress = 1) when the change in an individual regressor ranges from its approximate minimum to its maximum observed value, keeping all the other covariates constant at their means.[49]

The marginal effects presented in Table 9 reflect a measure of the impact of the regressors on the response variable. The predictor variables with the largest impact, in absolute terms, in Model 2 are invariably the financial ratios TLTA, COVERAGE, and TFOTL, in order of importance, with the NOCREDINT variable and macroeconomic indicators having the smallest impact on the expected instantaneous changes in the response variable while keeping all of the other covariates constant. This is also true when Model 2 was estimated in $t-2$. Interestingly, when market variables are added to the models based on financial ratios, ABNRET and MCTD are among the 4 largest marginal effects in absolute terms in Model 3; MCTD and ABNRET having the largest marginal effects in Model 3 in period $t-1$ and $t-2$, respectively. The present study also estimates the marginal effects for the 'Market only' model and the 'Market plus macroeconomic indicators' model, Model 4 and Model 5, in order to assess the changes in the response variable following a change in the specific market variables while keeping all the other covariates constant. These estimations confirm the previous results: in both market models, the variables ABNRET, MCTD, SIZE and PRICE have the largest marginal effects, followed by the macroeconomic indicators SHTBRDEF and RPI, in order of importance and in absolute terms. It can be therefore concluded that market variables do contain additional information very important to the prediction of financial distress. Moreover, market variables act as complements to financial ratios and market variables.

Presenting and analysing marginal effects for all the models in the study has filled a gap in the financial distress prediction literature that lacked a measure of the individual instantaneous contribution a change of a specific variable on the response variable (the financial distress indicator built for the present analysis), while keeping all the other regressors constant. Additionally, the present study goes further and presents the vector of predicted probabilities for all the individual variables' specific minimum and maximum ranges where they have the most impact in the probability of financial distress, while keeping all the other covariates constant at their respective means. Thus, Figs. 4–7 show the changes in predicted probabilities for accounting, macroeconomic and market variables, respectively, when the financial distress indicator is equal to 1. The importance of these figures is that they clearly show the magnitude as well as the directionality of each regressor reflected by the slope and inclination of the curves, plotted at various levels of the independent variables.

Fig. 5 shows the behaviour of the predicted probabilities for financial distress at different values of each of the financial statement ratios. It can be observed that the COVERAGE variable displays the steepest slope relative to the other ratios, indicating that a given change in the level of this variable[50] will have the largest impact on the predicted probability of financial distress, when all the other variables are kept constant at their means. The slope of the COVERAGE vector also shows that there is a negative relationship between the predicted probability and the level of the variable: there is an important decrease of the predicted probabilities of financial distress as the COVERAGE variable approaches its maximum estimation value (1). A very similar pattern can be observed for the TFOTL ratio reflecting the liquidity of a company: the slope also negatively relates the predicted probability of financial distress to the magnitude of the variable, although a change in its value produces a slightly smaller impact than the one observed when there is a change in the magnitude of COVERAGE, as shown by the slope of the vector. Changes in the magnitude of TLTA, on the other hand, are positively related to the predicted probability of financial distress, and can be considered as having the third most important impact among financial statement

[49] The SAS statistical package was also employed for this calculation.

[50] Reflecting the firm's ability to pay interest on outstanding debt.

Table 9
Marginal effects.

Variable	Model 1		Model 2		Model 3		Model 4	Model 5
	$t-1$	$t-2$	$t-1$	$t-2$	$t-1$	$t-2$	$t-1$	$t-1$
TFOTL	−3.375	−3.427	−3.211	−3.464	−4.059	−4.267		
TLTA	5.340	0.958	5.595	1.221	2.297	0.026		
NOCREDINT	−0.887	−0.781	−0.935	−0.794	−0.569	−0.400		
COVERAGE	−5.564	−5.983	−5.351	−5.878	−3.665	−4.129		
RPI			0.084	0.068	0.045	0.031		0.048
SHTBRDEF			0.792	0.994	0.475	0.439		0.431
PRICE					−0.393	−0.303	−0.724	−0.696
ABNRET					−4.301	−6.846	−7.446	−7.424
SIZE					−0.887	−0.188	−1.857	−1.769
MCTD					−4.872	−2.666	−4.119	−4.291
n	18,276	15,909	18,070	15,703	13,529	12,305	14,807	14,578

Notes: This table reports the marginal effects (in percentages) for the 'accounting only' model, the 'accounting plus macroeconomic indicators' model, the 'full' model including also market variables, or Model 1, Model 2 and Model 3, respectively. Additionally, marginal effects are generated for a 'market only' model and a 'market plus macroeconomic indicators' model, Model 4 and Model 5, for comparison purposes. n represents the number of observations. Marginal effects are intended to measure the expected instantaneous changes in the response variable (the financial distress indicator) as a function of a change in a specific predictor variable while keeping all the other covariates constant. The methodology used in the present study to generate the marginal effects consists of outputting the individual marginal effects estimated at each observation in the dataset and then calculating their sample average in order to obtain the overall marginal effect.

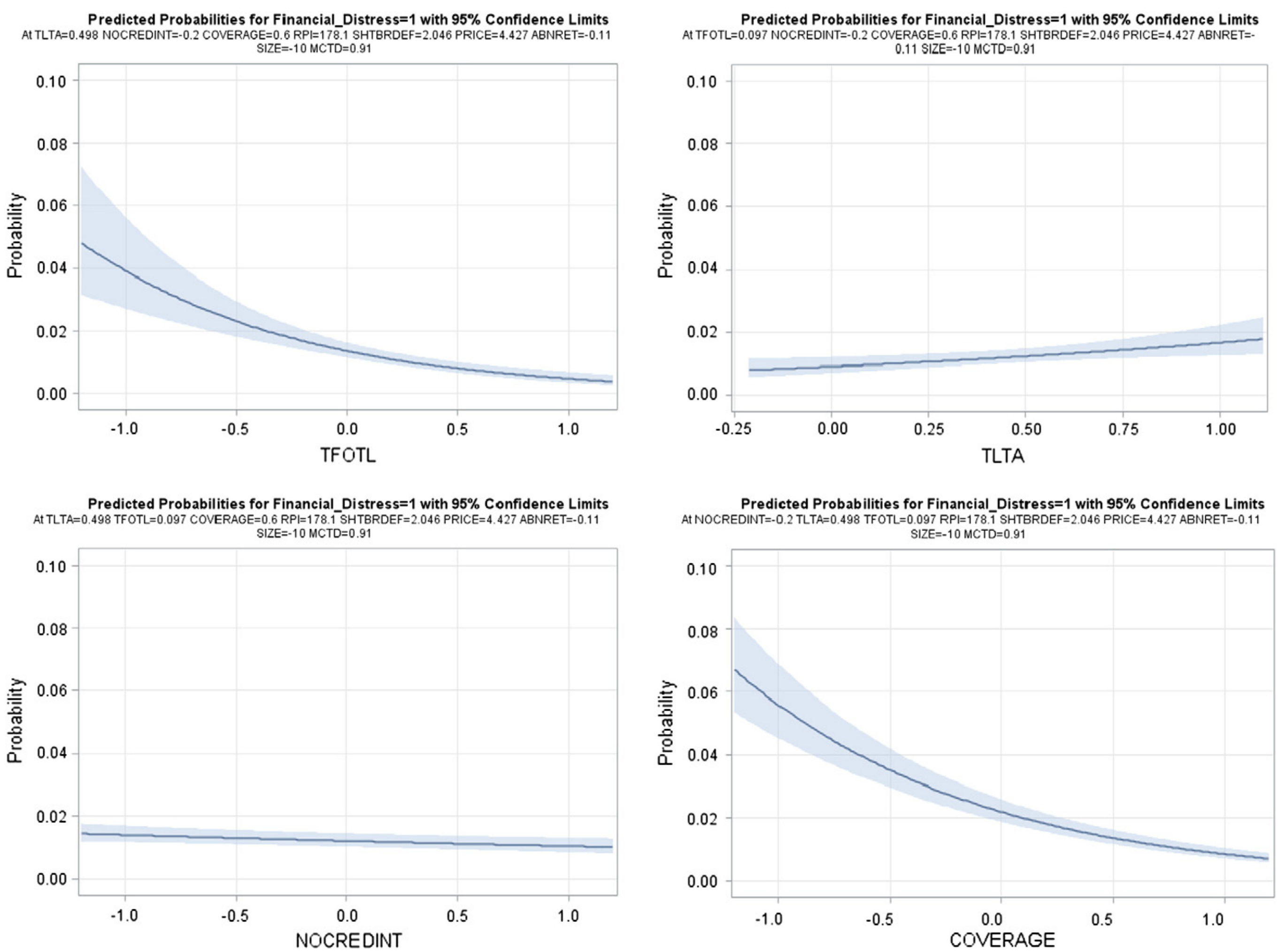


Fig. 5. Changes in predicted probabilities — financial statement ratios. The figure plots the vectors reflecting changes in predicted probabilities (for Financial Distress = 1) at different levels of the accounting independent variables Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE), keeping all the other covariates constant at their mean values (TFOTL = 0.097, TLTA = 0.498, NOCREDINT = −0.2, COVERAGE = 0.6, RPI = 178.1, SHTBRDEF = 2.046, PRICE = 4.427, ABNRET = −0.11, SIZE = −10, MCTD = 0.91). The computation was made taking into account all the variables included in the 'Full' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period $t-1$, the vectors estimated using the full model in $t-2$ have very similar shapes, so they were not reported in the present study.

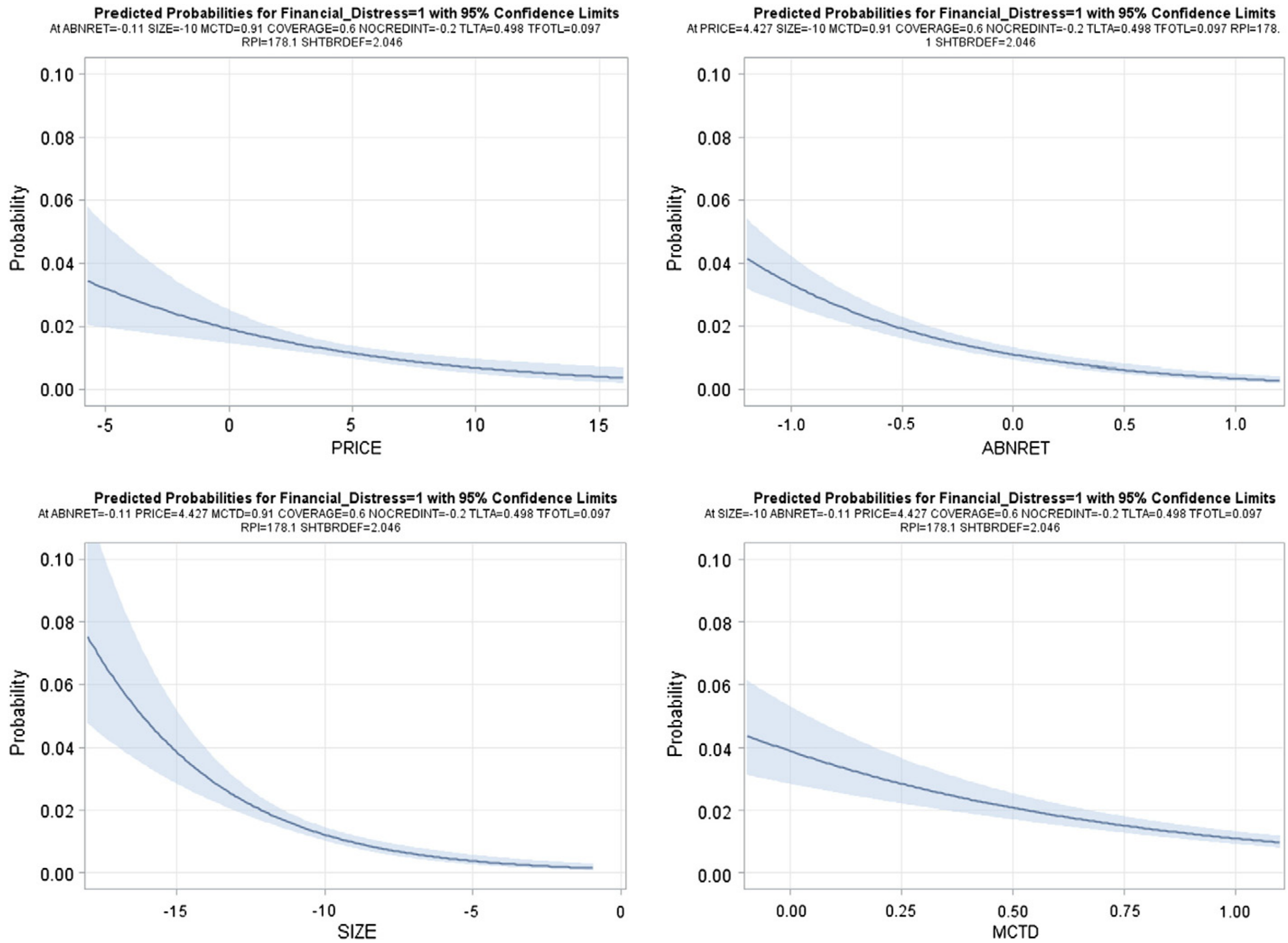


Fig. 6. Changes in predicted probabilities — market variables. The figure plots the vectors reflecting changes in predicted probabilities (for Financial Distress $= 1$) at different levels of the market independent variables Share Price (PRICE), Abnormal Returns (ABNRET), the relative Size of the company (SIZE), and the ratio Market Capitalisation to Total Debt (MCTD), keeping all the other covariates constant at their mean values (TFOTL $= 0.097$, TLTA $= 0.498$, NOCREDINT $= -0.2$, COVERAGE $= 0.6$, RPI $= 178.1$, SHTBRDEF $= 2.046$, PRICE $= 4.427$, ABNRET $= -0.11$, SIZE $= -10$, MCTD $= 0.91$). The computation was made taking into account all the variables included in the 'Full' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period $t-1$, the vectors estimated using the full model in $t-2$ have very similar shapes, so they were not reported in the present study.

ratios, followed by NOCREDINT, whose slope is almost flat, indicating a very small negative impact (Fig. 6).

As expected, all of the market variables show a negative relationship between variations in individual levels and predicted probabilities of financial distress. The covariate with the largest impact on the latter is SIZE, as the vector displays the steepest slope. It is followed by ABNRET, MCTD and PRICE, which is consistent with the output obtained from the calculation of marginal effects. Finally, variations in the magnitude of economic indicators are positively related to changes in the predicted probabilities of financial distress when all the other covariates are kept constant at their means. Interestingly, the vectors' slopes of the macroeconomic indicators RPI and SHTBRDEF are steeper than the financial statement ratios TLTA and COVERAGE, which could lead us to conclude that they have a larger impact on the predicted probability of financial distress than the estimates of marginal effects would suggest. However, this is hardly the case, as the ranges used to plot the slopes of the macroeconomic indicators are larger in absolute terms than those of the two financial statement ratios, which might explain the observed phenomenon.

5.2. Classification accuracy tables

Classification accuracy tables have been used in previous works as an additional tool to measure the predictive accuracy of the default/bankruptcy prediction models. The present study, however, employs a different and more appropriate methodology to estimate proportions of correct and incorrect classifications of financially and non-financially distressed firms. In order to classify a set of binary data, previous research works employ the same observations used to fit the model to estimate the classification error, resulting in biased error-count estimates. In other words, the widely-used 2×2 frequency tables' estimates, where correctly classified observations are displayed on the main diagonal of the table, are derived using all observations to fit the model. Therefore, the results are biased, as each observation has an effect on the model used to classify itself. One way of reducing the bias is 'to remove the binary observation to be classified from the data, re-estimate the parameters of the model, and then classify the observation based on the new parameter estimates.[51]' As it is clear that

[51] SAS Institute.

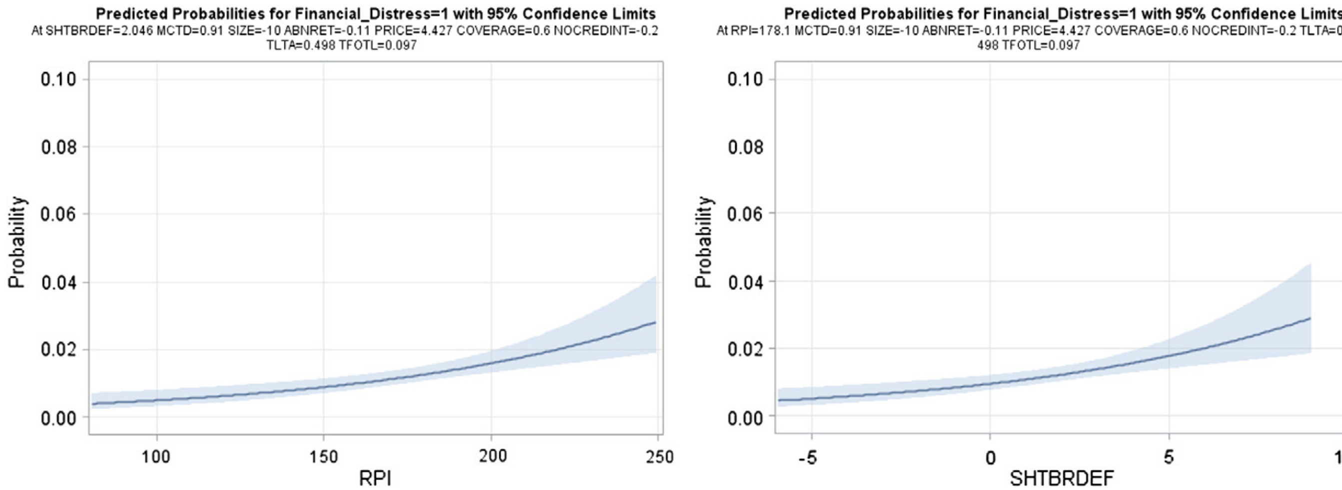


Fig. 7. Changes in predicted probabilities — macroeconomic indicators. The figure plots the vectors reflecting changes in predicted probabilities (for Financial Distress = 1) at different levels of the macroeconomic independent variables Retail Price Index (RPI), and the proxy for interest rates, the Deflated Short Term Bill Rate (SHTBRDEF), keeping all the other covariates constant at their mean values (TFOTL = 0.097, TLTA = 0.498, NOCREDINT = −0.2, COVERAGE = 0.6, RPI = 178.1, SHTBRDEF = 2.046, PRICE = 4.427, ABNRET = −0.11, SIZE = −10, MCTD = 0.91). The computation was made taking into account all the variables included in the 'Full' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period $t-1$, the vectors estimated using the full model in $t-2$ have very similar shapes, so they were not reported in the present study.

this method is rather expensive for very large datasets, the present study employs the logistic procedure that provides a less-expensive one step approximation to the preceding parameter estimates.[52]

In order to construct a bias-adjusted classification table, predicted financial distress event probabilities are estimated for each observation. If the predicted event probability exceeds or equals a given cutpoint value (whose real line is mapped onto [0,1]), then the observation is predicted to be in financial distress, otherwise, it is predicted to be a non-event or non-financially distressed. The probability levels chosen range from 0.020 to 0.120 in order to get high levels of Sensitivity and Specificity, combined as well as individually. The advantage of this methodology to construct classification tables is that it provides a useful tool to re-calibrate a distress prediction model with different probability cutpoints depending on the costs assigned to the Type I and II errors.

The present study measures the accuracy of the classification through its Sensitivity (the ability of the model to predict a financial distress event correctly) and Specificity (the ability of the model to predict a non-financial distress event correctly). In Table 10, the 'Correct' column shows the number of observations that were correctly predicted as financially distressed and non-financially distressed, respectively. The 'Incorrect' column presents the number of non-financially distressed observations that were incorrectly predicted as financially distressed, and the number of financially distressed observations that were incorrectly predicted as non-financially distressed, respectively. The 'Percentages' column exhibits the rate of correct classifications, the proportion of financial distress responses that were predicted to be financial distress events (Sensitivity, or the ability of the model to predict financial distress correctly), and the rate of non-financial distress responses that were predicted to be non-financial distress events (Specificity, or the ability of the model to predict non-financial distress correctly), respectively.

Biased-adjusted classification tables were calculated for Model 2 (the 'Accounting plus macroeconomic indicators' model) and Model 3 (the 'Full' model) in order to assess the increase in the classification accuracy when market variables are added to a model based on financial statement ratios (Panel A and panel B in Table 10, respectively). Furthermore, Table 10 also exhibits a classification table for Model 3 estimated in period $t-2$ in order to test whether the 'Full' model continues to be useful in predicting financial distress two years prior to the distress event, thus confirming its predictive accuracy. It can be concluded that the methodology employed was effective to confirm these two points: there is a considerable increase in classification performance from Model 2 to Model 3, meaning that market variables provide useful information not included in financial statement ratios or macroeconomic indicators. Furthermore, the improvement suggests that the three types of variables act as complementary, confirming the previous results obtained from the analysis of Areas under the Receiver Operating Characteristics Curve. The 0.060 probability level was chosen as an appropriate benchmark to perform a comparison between models for the following reasons: First, this level is equal to the rate of failed to healthy companies for which complete data made the computation of predicted probabilities possible. Second, this level produces the smallest gap between sensitivity and specificity percentages. Panels A, B, and C show that a probability level of 0.060 used as cutpoint, yields the combined highest predictive accuracy between Sensitivity and Specificity for the three models. The increase in predictive accuracy when market variables are added to the 'Accounting and macroeconomic indicators' model is equal to 5 percentage points as measured by the proportion of correct classifications in column 6 of Table 10, at the 0.060 probability level as cutpoint value; from 80 to 85% correct classifications in Model 2 and Model 3, respectively.

Furthermore, when Model 3 is estimated in period $t-2$, the rate of correct classifications decreases by only one percentage point relative to the same model estimated in period $t-1$, at the same 0.060 probability cutpoint: the correct classifications percentage is 85 in $t-1$, decreasing only marginally to 84 in $t-2$. This indicates that the 'Full' model is also very useful to predict financial distress two years prior to the event.

The present classification table also possesses the advantage of allowing a risk manager to calculate higher percentages of Sensitivity and Specificity individually. This is particularly useful as Type I and II

[52] http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_logistic_sect037.htm.

Table 10
Bias-adjusted classification table.

Probability level	Correct		Incorrect		Percentages		
	Distressed	Non-distressed	Distressed	Non-distressed	Correct	Sensitivity	Specificity
Panel A: Model 2 ($t-1$)							
0.020	841	12,282	4861	86	72.6	90.7	71.6
0.040	785	13,602	3541	142	79.6	84.7	79.3
0.060	**762**	**13,764**	**3379**	**165**	**80.4**	**82.2**	**80.3**
0.080	738	13,983	3160	189	81.5	79.6	81.6
0.100	701	14,275	2868	226	82.9	75.6	83.3
0.120	646	14,643	2500	281	84.6	69.7	85.4
Panel B: Model 3 ($t-1$)							
0.020	685	9455	3346	43	75.0	94.1	73.9
0.040	651	10,419	2382	77	81.8	89.4	81.4
0.060	**631**	**10,845**	**1956**	**97**	**84.8**	**86.7**	**84.7**
0.080	608	11,136	1665	120	86.8	83.5	87.0
0.100	584	11,342	1459	144	88.2	80.2	88.6
0.120	563	11,499	1302	165	89.2	77.3	89.8
Panel C: Model 3 ($t-2$)							
0.020	654	7793	3800	58	68.6	91.9	67.2
0.040	611	9305	2288	101	80.6	85.8	80.3
0.060	**576**	**9757**	**1836**	**136**	**84.0**	**80.9**	**84.2**
0.080	556	10,013	1580	156	85.9	78.1	86.4
0.100	532	10,205	1388	180	87.3	74.7	88.0
0.120	508	10,356	1237	204	88.3	71.3	89.3

Notes: This table reports a biased-adjusted classification table for predicted distress frequencies at different probability levels as cut-off values for Model 2 estimated in period $t-1$, and Model 3 estimated in period $t-1$ and $t-2$, in Panel A, B and C, respectively. The 'Correct' column shows the number of observations that were correctly predicted as financially distressed (Column 2) and non-financially distressed (Column 3), respectively. The 'Incorrect' column presents the number of non-financially distressed observations that were incorrectly predicted as financially distressed (Column 4), and the number of financially distressed observations that were incorrectly predicted as non-financially distressed (Column 5), respectively. The 'Percentages' column exhibits the rate of correct classifications (Column 6), the proportion of financial distress responses that were predicted to be financial distress events (Sensitivity, or the ability of the model to predict financial distress correctly, Column 7), and the rate of non-financial distress responses that were predicted to be non-financial distress events (Specificity, or the ability of the model to predict financial health correctly, Column 8), respectively.

errors are not equally weighted by practitioners. A false positive error is not as expensive as a false negative: the cost of firm predicted as financially distressed when it is in fact healthy, is less than the cost of a firm predicted as financially healthy when it is in fact financially distressed. Therefore, if this is the case, a risk manager would be more interested in increasing the rate of correctly classified financially distressed firms (Sensitivity), choosing a lower probability level as cutpoint.[53] This would be done, however, only at the cost of reducing the ability of the model to predict non-financial distress events correctly (Specificity). The present study presented the rates of Specificity and Sensitivity at different probability levels as cutpoints to show the practical use of this approach to measure the accuracy of a distress prediction model and its advantages in relation to the widely employed 2×2 frequency tables that implicitly give equal weights to Type I and Type II errors.

5.3. Model validation

In order undertake validation tests for model performance, the main database was divided in two sub-periods: 2001–2006 and 2007–2011. The first one corresponds to the period after the collapse of the information technology bubble, which took place during 2000–2001, and the second one is the period following the global financial crisis of 2007 to 2011. The 'Full' model was applied to the two sub-periods in order to test whether its predictive accuracy remain acceptable as measured by the Area Under the ROC Curve. Additionally, Model 3 was tested in period $t-1$ and $t-2$, in order to confirm whether the predictive accuracy holds when the model is estimated one year prior to the event of financial distress. As shown in Table 11, the predictive accuracy decreases only marginally when the model is tested with the two sub-period data. Interestingly, the model performs better in the 2007–2011 period than in the 2001–2006 period, which might be explained by the smaller number of observations of the former, and thus the lower amount of financial distress events to predict. The same analysis applies when the model is estimated in $t-2$. Nevertheless, the model retains a very high predictive accuracy overall.

5.4. Performance comparison benchmarks

The present study also tests the robustness of the models through a comparison between the three main Models presented (Model 1, 2, and 3), the classic Altman's (1968) model estimated employing logistic regression, the widely-used Altman's (1968) Z-score, and the

Table 11
Model validation — areas under the ROC curve.

	1980–2011	2001–2006	2007–2011
Model 3 in $t-1$	0.9190	0.9029	0.9123
Model 3 in $t-2$	0.8918	0.8807	0.8935

Notes: This table reports the model validation results for Model 3 estimated in period $t-1$ and $t-2$. The main data set was divided into two sub-periods. The first one, 2001–2006, corresponds to the period after the collapse of the information technology bubble, and the second one, 2007–2001, is the period that follows the global financial crisis that started in 2007. The predictive accuracy or the overall performance of the model is measured by the Area Under the Receiver Operating Characteristics Curve.

[53] In this case the predicted probability used as cutpoint would have to be lower than the 0.060 level.

Table 12
Logistic regression and artificial neural networks performance comparison results — areas under the ROC curve.

Measure	Model 1	Model 2	Model 3	Altman	Multilayer perceptron
Panel A: models' performance in t − 1					
AUC	0.8718	0.8763	0.9190	0.8517	0.9250
Gini rank coefficient	0.7436	0.7526	0.8380	0.7034	0.8500
Kolmogorov–Smirnov	0.5949	0.6021	0.6704	0.5627	0.6800
Panel B: models' performance in t − 2					
AUC	0.8523	0.8514	0.8918	0.8229	0.9120
Gini rank coefficient	0.7046	0.7028	0.7836	0.6458	0.8240
Kolmogorov–Smirnov	0.5637	0.5622	0.6269	0.5166	0.6592

Notes: This table reports model performance statistics. Panel A shows measures for the models estimated in period $t-1$ and Panel B displays the same measures for the models estimated in $t-2$. Models 1, 2, 3 and Altman's model were estimated using the panel logit methodology. In addition, Model 3 was estimated using the neural networks methodology (multilayer perceptron). Model 1 is the 'accounting only' model, Model 2 is the 'accounting plus macroeconomic variables' model, Model 3 is the 'full' model, including market variables in addition to the variables in Model 2. The Altman Model includes the following accounting ratios: Working Capital to Total Assets, Retained Earnings to Total Assets, Earnings Before Interest and Taxes to Total Assets, Market Value of Equity to Book Value of Total Debt, and Sales to Total Assets. The first measure, the Area Under the Receiver Operating Characteristics Curve (AUC), is a direct measure of the predictive accuracy of the models estimated using the logit methodology; Gini coefficients and Kolmogorov–Smirnov statistic are also presented.

comprehensive model estimated using artificial neural networks (multilayer perceptron). Three techniques for the prediction of financial distress are therefore employed to test the performance of our model. Table 12 presents a comparison of the performance of the 'Accounting only' model, the 'Accounting plus macroeconomic indicators' model, the 'Full' model, Altman's (1968) model estimated using logistic regression, and the 'Full' model estimated using artificial neural networks, as measured by the Area under the Receiver Operating Characteristics Curve (AUC), Gini rank coefficients, and Kolmogorov–Smirnov statistics.

Table 12 shows that when the Altman model is estimated employing the panel logit methodology, it displays a predictive accuracy similar (marginally inferior) to the 'Accounting only' model (Model 1) and the 'Accounting plus macroeconomic indicators' model (Model 2), as measured by the Area Under the ROC Curve. This is as expected, as Model 1, Model 2 and the Altman model are accounting-based models, which makes the comparison appropriate. Model 2, which includes macroeconomic indicators, yields the best performance among the accounting-based models (AUC = 0.8763), followed by Model 1 (AUC = 0.8718), and Altman's (1968) model (0.8517) in $t-1$. This same pattern is reproduced when the models are estimated in $t-2$, the only difference being, as previously discussed, that Model 1 performance is marginally higher than Model 2, indicating that the information contained in accounting variables is more relevant to the prediction of failure/financial distress than the information obtained from macroeconomic variables when the model is estimated with data two years prior to the event of failure/financial distress.

Following the comparative approach between statistical methods and intelligent techniques in Olson, Delen, and Meng (2012), Tseng and Hu (2010), Cho, Kim, and Bae (2009), and Kumar and Ravi (2007), the present study also estimates Model 3 (the 'Full' model) using artificial neural networks[54] in order to perform an additional test of the performance of our model. Moreover, logistic regression is a prevalent statistical methodology employed as benchmark for comparison purposes by these authors. The present study employs the multilayer perceptron,[55] which is the most common architecture in artificial neural networks (Alfaro, García, Gámez, & Elizondo, 2008[56]). In this regard, Table 12 shows that the comprehensive Model 3 estimated using artificial neural networks (multilayer perceptron) yields the highest overall performance among all models with an AUC equal to 0.9250, followed by Model 3 estimated using logistic regression with an AUC equal to 0.9190. The marginally superior performance of artificial neural networks is consistent with previous research; neural networks comprise highly complex sets of node connections and weights that can be obtained from software (Olson et al., 2012), and overcome the restrictions entailed by traditional statistical methodologies (logistic regression included) such as the assumption of linearity, normality, independence among predictor variables, for instance (Yang, You, & Ji, 2011). However, Table 12 shows that the difference in performance is marginal; moreover, logistic regression has the advantage of providing a form that can be understood and transported quite easily, unlike neural networks, which lack 'transparency (seeing what the model is doing, or comprehensibility) and transportability (being able to easily deploy the model into a decision support system for new cases)' (Olson et al., 2012[57]).

Table 13 presents a biased-adjusted classification table for predicted distress frequencies at different probability levels as cut-off values when the models are estimated in period $t-1$. Models 2, 3, and Altman's model are estimated using the panel logit methodology (Sections A, B, and C respectively). In addition, Model 3 was estimated using the neural networks methodology (multilayer perceptron) in section D. When the 0.060 level is used as a benchmark to compare the predictive accuracy of Model 2 and Model 3 relative to the Altman model, it can be observed that Model 2 possesses a marginally higher predictive accuracy than Altman's (1968) model: the overall rate of correct predictions for the Altman model is 77.8%, following closely the predictive accuracy of Model 2, which is equal to 80.4%. On the other hand, the 'Full' model displays a rate of correct predictions equal to 86.7%, which is significantly superior to both accounting-based models.

Finally, when Model 3 is estimated using artificial neural networks (multilayer perceptron), it can be observed that it yields a very similar classification accuracy to Model 3 in $t-1$; with regard to the overall accuracy, Model 3 (logistic regression) shows a marginally higher performance of only 10 basis points (0.10%) approximately at the three probability levels presented. Table 13 also shows that, as to the performance in correctly predicting financially distressed firms, the neural networks methodology is marginally superior (by less than 1 percentage point) to the logistic regression methodology. The opposite is true as to the rate of correct classifications of healthy firms: the logistic methodology is marginally superior to the neural networks technique. Overall, it can be concluded that the performances of the logistic regression model and the neural networks model are almost identical, as the differences in predictive accuracy are very small, with the neural networks model outperforming the logit model for the prediction of failed/distressed firms, although by a very small margin (less than 1 percentage point approximately), which is consistent with the results obtained through the analysis of their respective areas under the ROC curves in Table 12.

Table 14 shows Altman's Z-score classification table to discriminate between healthy and financially distressed companies employing the

[54] For details regarding the fitting of the artificial neural network model in the present study, see Appendix A.

[55] The multilayer perceptron is a feedforward network that consists of an input layer, an output layer, and a number of hidden layers.

[56] p. 116.

[57] p. 464.

Table 13
Bias-adjusted classification table — logistic regression and artificial neural networks comparison.

Probability level	Correct		Incorrect		Percentages		
	Distressed	Non-distressed	Distressed	Non-distressed	Correct	Sensitivity	Specificity
Panel A: Model 2 (t − 1)							
0.040	785	13,602	3541	142	79.6	84.7	79.3
0.060	**762**	**13,764**	**3379**	**165**	**80.4**	**82.2**	**80.3**
0.080	738	13,983	3160	189	81.5	79.6	81.6
Panel B: Model 3 (t − 1)							
0.040	651	10,419	2382	77	81.8	89.4	81.4
0.060	**631**	**10,845**	**1956**	**97**	**84.8**	**86.7**	**84.7**
0.080	608	11,136	1665	120	86.8	83.5	87.0
Panel C: Altman model (t − 1)							
0.040	1046	12,584	5887	170	69.2	86.0	68.1
0.060	**944**	**14,365**	**4106**	**272**	**77.8**	**77.6**	**77.8**
0.080	854	15,359	3112	362	82.4	70.2	83.2
Panel D: multilayer perceptron (t − 1)							
0.040	659	10,390	2411	69	81.7	90.5	81.2
0.060	**640**	**10,818**	**1983**	**88**	**84.7**	**87.9**	**84.5**
0.080	620	11,098	1703	108	86.6	85.2	86.7

Notes: This table reports a biased-adjusted classification table for predicted distress frequencies at different probability levels as cut-off values when the models are estimated in period $t-1$. Models 2, 3, and Altman's model are estimated using the panel logit methodology (Panels A, B, and C respectively). In addition, Model 3 was estimated using the neural networks methodology (multilayer perceptron) in Panel D. The 'Correct' column shows the number of observations that were correctly predicted as financially distressed and non-financially distressed, respectively. The 'Incorrect' column presents the number of non-financially distressed observations that were incorrectly predicted as financially distressed, and the number of financially distressed observations that were incorrectly predicted as non-financially distressed, respectively. The 'Percentages' column exhibits the rate of correct classifications, the proportion of financial distress responses that were predicted to be financial distress events (Sensitivity, or the ability of the model to predict financial distress correctly), and the rate of non-financial distress responses that were predicted to be non-financial distress events (Specificity, or the ability of the model to predict financial health correctly), respectively.

widely-used cutoff values: a company is classified as 'financially healthy' if its Z-score is greater than 2.99 and as 'financially distressed' if its Z-score is less than 1.81; additionally, following Altman (2000), a company is classified as 'financially distressed' if its Z-score is less than 2.67 (in parenthesis). From Table 14, it can be conclude that this method shows an impressive classification accuracy with regard to financially distressed firms. However, the Z-score performance is less impressive to correctly classify safe or financially healthy companies, identifying a high proportion of healthy firms as distressed. Even if an error of the first kind or Type I error (false positive) is not as costly as an error of the second kind (false negative), the present analysis shows that our model for UK listed companies has some advantages over the Z-score model. First, when comparing the predictive accuracy, it can be observed that, taking the 0.060 predicted probability level as cut-off, the 'full' model displays a superior performance for the classification of distressed firms: it correctly classified 87% of distressed companies while the Z-score model correctly classified 81%. Second, using the same 0.060 predicted probability level as cut-off, the 'full' model displays an almost equal predictive accuracy with regard to financially healthy companies (sensitivity is equal to 85%), which makes the model reliable for the prediction of both distressed and financially healthy companies. Third, in technical terms, it is very straightforward to modify the predicted probability level employed as cut-off in order to minimise Type I or Type II errors (through a trade-off) depending on the researcher's/risk manager's objectives.

Table 14
Altman's Z-score classification table.

Observed	Predicted			
	Healthy	Distressed	Total	% Correct
Healthy	9178	8278	17,456	52.58%
Distressed	234	899 (997)	1133	79.35% (80.99%)
Overall percent				54.21%
Average percent				65.96%

Notes: This table shows the classification accuracy results for Altman's Z-score model. In order to estimate the rate of correct predictions, three different cut-offs were employed: a company was classified as financially healthy if its Z-score was greater than 2.99, and it was classified as failed/financially distressed if its Z-score was less than 1.81. The numbers in parenthesis represent the firms classified as failed/financially distressed when using a cut-off of 2.67, following Altman (2000).

6. Conclusions

This study offers a comparison of the classification accuracy and predictive power of three types of variables (financial statement ratios, macroeconomic indicators and market variables) in a logit model for quoted companies in the United Kingdom based on a financial definition of firm distress. It contributes to the default prediction literature by, first, using a finance-based definition of distress complemented with a technical approach built using information provided by the London Share Price Database. The advantage is that the definition of financial distress presented in this study is not contingent upon its ultimate legal consequence: bankruptcy, as in most of the previous prediction literature. A wider, ex ante approach is employed, in order to detect early stages of financial distress with a high degree of reliability that could be useful to practitioners to avert the high costs associated with a bankruptcy filing. Second, a large dataset was built merging different types of information from data sources widely used in the academic as well as in the industry fields. Therefore, this study relies not only on independent variables used in previous research works; but it also used a multi-level theoretical and empirical procedure to test and select the variables with the highest contribution to the overall accuracy of the model. Furthermore, the study presents, unlike most studies in the field of default prediction, a theoretically-based justification for the use of each of the retained variables in the final models. The result is a model for the prediction of financial distress in the United Kingdom for quoted companies that, with a small number of variables, displays a very high classification and prediction accuracy relative to previous research works. Third, and perhaps most importantly, the study tests, for the first time in financial distress prediction models for quoted companies in the UK, the relative contributions (individual and as groups) of the three types of variables to the predictive accuracy of the model: financial, macroeconomic and market variables. Prior research has tested the ability of market variables to predict bankruptcy employing methodologies such as the Black and Scholes contingent claims or option-based approach. However, the results obtained from these models (that entail numerous restrictive assumptions) have been controversial. Many efforts have been carried out to demonstrate the superiority of market-based models over accounting-based models and vice versa. To this point, the default prediction literature is characterised by a competing approach, where there is a clear division line between market and accounting variables. The present study adopts a different approach where the use of these types of variables is not mutually exclusive. It is tested whether the market variables (dependent, in some measure, upon the same financial information) add information that is not contained in financial statements and therefore act as complement in default prediction models. The results presented in this study clearly indicate that this is the case. The considerable increase of the Area Under the Receiver Operating Characteristics (ROC) Curve (among several other formal measures), from 0.88 to 0.92 in a model estimated in $t-1$ and from 0.85 to 0.89 in a model estimated in $t-2$, that followed the incorporation of market variables in an accounting model indicates that they contain information that is not included in financial statement ratios. A comparison of areas under correlated ROC curves performed using a non-parametric method, and the estimation of biased-adjusted classification tables confirmed these results. In addition, when a full model was estimated in $t-2$ to test the real predictive accuracy of the model, three out of four market variables retained their statistical significance, the same proportion as the financial ratios, which indicates that the variables included in the model are consistent. Interestingly, Hosmer and Lemeshow goodness-of-fit tests for binary response logistic models suggest that the 'full model' fitted with market variables is an adequate model, unlike the 'accounting only' or 'accounting plus macroeconomic variables' model. On the other hand, results are less conclusive for macroeconomic variables, which contribute only marginally to the overall classification accuracy of the model. Finally, the estimation of marginal effects fills an important gap in the default prediction literature by presenting expected instantaneous changes in the response variable as function of a change in a specific predictor variable while keeping all the other covariates constant, which is very useful to the interpretation of the individual effects.

Appendix A

A.1. Fitting of Model 3 using the artificial neural networks methodology (multilayer perceptron)

Neural networks.

Network information.

Input layer covariates: 1. TFOTL, 2. TLTA, 3. NOCREDINT, 4. COVERAGE, 5. RPI, 6. SHTBRDEF, 7. PRICE, 8. ABNRET, 9. SIZE, 10. MCTD

Hidden layers.

Number of hidden layers: 1

Number of units in hidden layer 1 (excluding the bias unit): 4

Activation function: hyperbolic tangent

Output layer.

Dependent variable: financial distress indicator

Number of units: 2

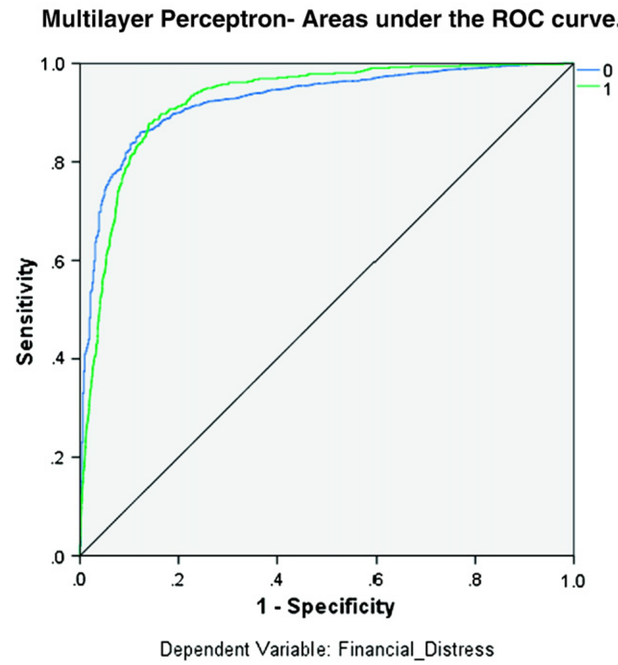
Activation function: Softmax

Error function: cross-entropy

Casing processing summary.

Training: 70.2%

Holdout: 29.8%



Area Under the Receiver Operating Characteristics Curve when:

Financial distress indicator $(1) = 0.925$

Financial distress indicator $(0) = 0.925$.

A.2. Estimation of Model 3 with industry controls

Industry code construction.

Industry code	SIC code	Industry name
1	<1000	Agriculture, forestry and fisheries
2	1000 to less than 1500	Mineral industries
3	1500 to less than 1800	Construction industries
4	2000 to less than 4000	Manufacturing
5	4000 to less than 5000	Transportation, communication and utilities
6	5000 to less than 5200	Wholesale trade
7	5200 to less than 6000	Retail trade
8	6000 to less than 6800	Finance, insurance, and real estate
9	7000 to less than 8900	Service industries
10	9100 to less than 10,000	Public administration

Notes: This table shows the SIC codes corresponding to the Industry classification used in the present study to control for firm sector. Four-digit SIC codes for each firm were employed for the partitioning into ten major industrial sectors. The corresponding names of the industrial groupings are presented in the last column of the table. Firm belonging to the 'finance, insurance and real estate sector' were excluded from the analysis. Following Chava and Jarrow (2004), SIC codes were chosen for this study because they are the most widely available industry classifications for the present sample period.

Logit regression of financial distress indicator on predictor variables with industry dummies.

Variable	Model 1		Model 2		Model 3		Model 4	Model 5
	$t-1$	$t-2$	$t-1$	$t-2$	$t-1$	$t-2$	$t-1$	$t-1$
TFOTL	−0.8081**	−0.7355**	−0.7684**	−0.7326**	−1.1047**	−1.0056**		
	(6.67)	(6.14)	(6.31)	(6.09)	(6.62)	(6.24)		
TLTA	1.1752**	−0.0109	1.2222**	0.0347	0.6149**	−0.1022		
	(6.70)	(0.06)	(6.95)	(0.19)	(2.58)	(0.42)		
NOCREDINT	−0.2183**	−0.1766**	−0.2313**	−0.1795**	−0.1440**	−0.0968*		
	(4.87)	(3.94)	(5.16)	(4.00)	(2.65)	(1.85)		
COVERAGE	−1.3580**	−1.3124**	−1.3093**	−1.2797**	−0.9805**	−0.9885**		
	(23.20)	(22.68)	(22.31)	(21.95)	(14.25)	(14.44)		
RPI			0.0211**	0.0158**	0.0123**	0.0079**		0.0109**
			(8.78)	(6.30)	(4.38)	(2.78)		(4.37)
SHTBRDEF			0.1889**	0.2141**	0.1258**	0.1025**		0.0991**
			(6.44)	(5.68)	(3.81)	(2.43)		(3.42)
PRICE					−0.1022**	−0.0740**	−0.1650**	−0.1588**
					(3.87)	(2.88)	(6.60)	(6.28)
ABNRET					−1.1505**	−1.6262**	−1.7593**	−1.7364**
					(9.53)	(13.60)	(15.33)	(15.06)
SIZE					−0.2469**	−0.0476	−0.4484**	−0.4242**
					(7.44)	(1.55)	(15.56)	(14.55)
MCTD					−1.2621**	−0.6109**	−0.9678**	−0.9878**
					(7.26)	(3.05)	(6.87)	(6.98)
Constant	−3.9969**	−2.8718**	−8.9642**	−6.4594**	−7.2825**	−3.7900**	−19.8216	−20.4127
	(3.48)	(2.44)	(6.96)	(4.89)	(4.54)	(2.40)	(0.03)	(0.05)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0934	0.0951	0.0977	0.0978	0.1428	0.1277	0.1027	0.1041
Max-rescaled R^2	0.2826	0.2687	0.2936	0.2743	0.4169	0.3573	0.2996	0.3009

Notes: This table reports results from logit regressions of the financial distress indicator on the predictor variables. The models were computed for two periods: using the accounts, market and macroeconomic data from the year prior to the observation of the financial distress event ($t-1$), and the accounts, market and macroeconomic data from two years prior to the observation of the financial distress event ($t-2$) in order to confirm their predictive ability in addition to their discriminating power. Additionally, results are also presented for a 'Market' model that incorporates market variables in $t-1$ for comparison purposes. The absolute value of Z-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%–1%.

Model performance measures — models with indus

Measure	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A: models' performance in $t-1$					
AUC	0.8719	0.8775	0.9194	0.8723	0.8735
Gini rank coefficient	0.7438	0.7550	0.8388	0.7446	0.7470
Kolmogorov–Smirnov	0.5950	0.6040	0.6710	0.5957	0.5976
Cox & Snell's R^2	0.0934	0.0977	0.1428	0.1027	0.1041
Nagelkerke's R^2	0.2826	0.2936	0.4169	0.2996	0.3009
χ^{2*} (4, 6, 10, 4, 6)	1792.53 ($p<.0001$)	1857.77 ($p<.0001$)	2084.05 ($p<.0001$)	1604.07 ($p<.0001$)	1602.42 ($p<.0001$)
Hosmer & Lemeshow goodness-of-fit test					
χ^2 (8)	76.6702	56.0823	11.0757	16.7956	14.9459
Pr > χ^2	<.0001	<.0001	0.1974	0.0323	0.0602
Panel B: models' performance in $t-2$					
AUC	0.8548	0.8553	0.8922	0.8371	0.8368
Gini rank coefficient	0.7096	0.7106	0.7844	0.6742	0.6736
Kolmogorov–Smirnov	0.5677	0.5685	0.6275	0.5394	0.5389
Cox & Snell's R^2	0.0951	0.0978	0.1277	0.0834	0.0843
Nagelkerke's R^2	0.2687	0.2743	0.3573	0.2336	0.2333
χ^{2*} (4, 6, 10, 4, 6)	1589.11 ($p<.0001$)	1616.09 ($p<.0001$)	1680.4646 ($p<.0001$)	1186.2039 ($p<.0001$)	1175.0079 ($p<.0001$)
Hosmer & Lemeshow goodness-of-fit test					
χ^2 (8)	77.4006	36.4974	10.3433	14.7841	11.3724
Pr > χ^2	<.0001	<.0001	0.2418	0.0635	0.1815

Notes: This table reports model performance statistics. Section A shows measures for the five models estimated in period $t-1$ and Section B displays the same measures for all of the models estimated in $t-2$. Model 1 is the 'accounting only' model, Model 2 is the 'accounting plus macroeconomic variables' model, Model 3 is the 'full' model, including market variables in addition to the variables in Model 2, Model 4 is the 'market only' model, and Model 5 is the 'market plus macroeconomic variables' model. The first measure is a direct measure of the predictive accuracy of models estimated using the logit methodology, the Area Under the Receiver Operating Characteristics Curve (AUC); Gini coefficients, Kolmogorov–Smirnov statistics, Cox and Snell *R*-squared, Nagelkerke's Max-rescaled *R*-squared and the models' Chi-squared are also presented. Additionally Hosmer and Lemeshow goodness-of-fit statistics are displayed. * the parenthesis following the model's χ^2 represent the degrees of freedom for each estimated model: 4 for Model 1, 6 for Model 2, 10 for Model 3, 4 for Model 4, and 6 for Model 5.

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